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Abstract

We construct a tractable multi-market equilibrium model designed to evaluate alternative biofuel policies. The model integrates the US agricultural sector with the energy sector and it explicitly considers both US ethanol and biodiesel production. The model provides a structural representation of the renewable fuel standard (RFS) policies, and it uses the arbitrage conditions defining the core value of renewable identification number (RIN) prices to identify the relevant competitive equilibrium conditions. The model is parameterized, based on elasticities and technical coefficients from the literature, to represent observed 2015 data. The model is simulated to analyze alternative scenarios, including: repeal of the RFS; projected 2022 RFS mandates; and, optimal (second best) mandates. The results confirm that the current RFS program considerably benefits the agriculture sector, but also leads to overall welfare gains for the United States (mostly via beneficial terms of trade effects). Implementation of projected 2022 mandates, which would require further expansion of biodiesel production, would lead to a considerable welfare loss (relative to 2015 mandate levels). Constrained (second-best) optimal mandates would entail more corn-based ethanol and less biodiesel than currently mandated.

***Key words**:* Biodiesel, biofuel policies, carbon tax, ethanol, greenhouse gas emissions, mandates, renewable fuel standard, RINs, second best, welfare.

JEL codes: Q2, H2, F1

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Over the last decade the United States has implemented major policies to promote biofuel use. The key provisions, set forth in the Energy Independence and Security Act (EISA) of 2007, are centered on the so-called Renewable Fuel Standard (RFS) which mandates certain amounts of renewable fuels to be blended into the US transportation fuel supply. These ambitious RFS "mandates" have been rationalized as pursuing a variety of objectives, including reduction of GHG emission and reduction of the US dependence on foreign energy sources (Moschini, Cui and Lapan 2012). Arguably, however, one of their most important impacts has been on agriculture. By sizably expanding demand for some agricultural products (e.g., corn to produce ethanol), the RFS is credited with having contributed substantially to increased commodity prices (Wright 2014; de Gorter, Drabik and Just 2015). These price increases have benefited farmers, and led to large land price increases, but biofuel policies' impact on land use has led to controversies, including the food versus fuel debate (Rosegrant and Msangi 2014) and whether biofuels yield actual net environmental benefits (Searchinger et al. 2008). In addition, development and production of cellulosic biofuel—one of the RFS's signature features—has severely lagged the mandates schedule set out in EISA. Furthermore, the current economic environment of relatively low oil prices, coupled with an unexpectedly strong domestic expansion of fossil fuel production, makes the energy security argument somewhat moot. The RFS remains controversial, and there is considerable interest in a comprehensive assessment of the current and future economic impacts of the RFS (Stock 2015).

In this article we construct a tractable multi-market competitive equilibrium model suitable to evaluate alternative biofuel policies. The model, which integrates the US agricultural sector with the energy sector, pays particular attention to a careful structural representation of the RFS biofuel support policies, and it is amenable to calibration and simulation to produce theoretically-consistent estimates of the market and welfare impacts of these policies. Unlike previous analyses that focused exclusively on ethanol (e.g., de Gorter and Just 2009, Cui et al. 2011), we develop a model that captures all of the various mandates envisioned by the RFS (Schnepf and Yacobucci 2013). These mandates are enforced by the US Environmental Protection Agency (EPA) via Renewable Identification Numbers (RINs), which are tradeable. A novel contribution of this article is to show how the arbitrage conditions for RIN prices derived from the behavior of distributors that blend biofuels with fossil fuels, including the RIN price inequalities implied by the hierarchical structure of the RFS mandates, can be embedded in a competitive equilibrium model.

One of the fault lines of the current RFS implementation is the rising role of biodiesel (Irwin and Good 2016). Insofar as biodiesel may be the biofuel of choice to meet the advanced biofuel portion of the RFS mandates, as suggested by recent EPA rulemakings (EPA 2016), an economic evaluation of current and prospective US biofuel policies needs to consider the interactions between US ethanol and biodiesel production. The model we present captures this essential connection by an explicit system representation of the feedstock used in biofuel production. For conventional ethanol produced in the United States, corn is the chosen feedstock in virtually all plants. Biodiesel production, on the other hand, uses a variety of feedstocks, including animal fats, recycled fats (yellow grease) and vegetable oils. The latter are the most important primary input, accounting for about 71% of biodiesel feedstock in 2015, with soybean oil being the most widely used (almost three fourths of all vegetable oils used in biodiesel production). Given the constraints on the availability of other more marginal feedstocks (Brorsen 2015), we assume that further expansions of biodiesel production would have to rely on redirecting vegetable oils from other uses. In this article, therefore, we develop a structural model of ethanol production from corn and biodiesel production from soybean oil.[1] The model captures the competition of primary agricultural products for scarce land, can trace the impact of biofuel mandates on equilibrium prices at various market levels, and can produce a coherent welfare assessment of the overall impact of RFS mandates.

The topic of this article is of considerable importance from a policy perspective. Biofuel policies, and the future of the RFS mandates, while likely to remain controversial, have a crucial impact on the agricultural sector (Cui et al. 2011, Pouliot and Babcock 2016). We find that the RFS has indeed proved to be a remarkably effective tool for farm support. Relative to the scenario of no biofuel policies, the 2015 level of mandates entails a 34% increase in corn price and a 9% increase in soybean price. The mandates' impact on energy prices is smaller in absolute terms, with crude oil price decreased by 1.4%. Because the United States is a net importer of crude oil, and a net exporter of corn and soybean products, these terms of trade effects contribute significantly to the finding that, overall, the welfare impact of the RFS has been positive. The RFS impact on reducing carbon emission, on the other hand, turns out to be nil once we account for the leakage effect (due to the induced increase in the rest of the world's fossil fuel consumption). Aggregate welfare at current mandate levels is larger than in the "No RFS" scenario by about $2.6 billion. To further improve welfare from the 2015 mandate levels, the model suggests that corn ethanol production should be increased, whereas biodiesel production should be decreased. The additional welfare gains from such constrained optimal mandates, however, are somewhat limited. Finally, implementation of the 2022 RFS statutory mandate levels—adjusted for a projected realistic expansion of cellulosic biofuels, consistent with EPA's recent waivers—would lead to sizeable welfare losses.

The RFS: Current and Prospective Mandates

The biofuel mandates of the RFS codified by EISA considerably extended the earlier provisions of the 2005 Energy Policy Act (Schnepf and Yacobucci, 2013). This legislation laid out a hierarchical set of quantitative minimum requirements for different types of biofuels, as well as a schedule for these mandates to increase over time, with final mandate levels being reached in 2022. The RFS defines an overall "renewable fuel" mandate, to be met with qualifying biofuels that achieve at least a 20% reduction in greenhouse gas (GHG) emissions (relative to fossil fuel), on a lifecycle basis. Furthermore, the RFS specifies a number of nested mandates as subsets of the overall renewable fuel mandate. The largest sub-component is that of "advanced biofuels." Such biofuels must achieve at least a 50% GHG emission reduction (relative to the conventional fuel) and encompass a variety of biofuels, including sugarcane ethanol and biodiesel (but corn-based ethanol is excluded). A portion of the advanced biofuel mandate is explicitly reserved for biomass-based diesel (biodiesel for short). The largest portion of the advanced biofuel mandate was supposed to be accounted for by cellulosic biofuels, identified as reaching a GHG emission reduction of at least 60% relative to the conventional fuel.

The EPA is responsible for implementing the RFS. To do so, prior to each year the EPA determines the fractional requirements that "obligated parties" (e.g., importers and refiners of fossil fuels) have to meet. These fractional requirements are calculated so that the mandates volumes of biofuel are achieved, given expected demand conditions. The fractional requirements determine the individual parties' renewable volume obligations (RVOs), given their sales of transportation fossil fuel. As noted earlier, these RVOs are enforced via the RIN system.[2] In addition to setting appropriate fractional requirements each year to implement the scheduled RFS mandates, the EPA has had to contend with the essential failure of cellulosic biofuel production: technology and production capacity are nowhere close to permit the fulfillment of the ambitious mandates envisioned by EISA. Hence, in the last several years, the EPA has exercised its waiver authority and drastically reduced the statutory RFS mandates accordingly.

Table 1 reports RFS mandate levels for the years 2015-2017, and for year 2022 (when biofuel mandates are supposed to reach their final levels). The columns labeled "EISA" contains the statutory mandates, for the overall renewable fuel and its subcomponents: advanced biofuel, biodiesel and cellulosic biofuel. It is useful to supplement these statutory mandates, reported in the first four rows of table 1, with two additional "implied" mandates. Note that there is no explicit mandate for corn-based ethanol. But given that this biofuel is the most cost-effective, at present, the implicit mandate for corn-based ethanol can be obtained as the difference between the renewable fuel mandate and the advanced biofuel mandate. This is reported in the last row of table 1, which shows that corn-based ethanol is effectively capped by EISA to a maximum of 15 billion gallons (from 2015 onward). Also, a portion of the advanced biofuel mandate, not reserved for cellulosic biofuels, can be met by a variety of biofuels (including sugarcane ethanol and biodiesel). This implied "non-cellulosic advanced" biofuel mandate, computed as the difference between advanced biofuel mandates and cellulosic biofuel mandate, is reported in the second-last row of table 1.

The columns labeled "EPA" reflect the agency's exercise of its waiver authority. It seems clear that the EPA has been systematically and drastically reducing the cellulosic biofuel mandate to levels that are feasible given current capacity, and simultaneously scaling back the overall renewable fuel mandate. At the same time, EPA rulemaking shows a clear intention to abide by the statutory mandates for the other components of the RFS. Also, the EPA is clearly signaling that biodiesel provides the avenue for meeting this non-cellulosic advanced biofuel mandate. The 2017 biodiesel mandate is almost sufficient to satisfy the other advanced biofuel mandates.[3] From these observations, we generated a reasonable projection of how the 2022 statutory mandates may be adjusted, and this is reported in the last column of table 1. This projection assumes that: (i) the non-cellulosic portion of the advanced biofuel mandate (5 billion gallons) will be fully implemented; (ii) the cellulosic biofuel mandate will continue to be scaled down based on available capacity (our projection relies on a linear trend of past EPA rulemakings); and, (iii) the overall renewable fuel mandate will be set so that, given (i) and (ii), the implied corn-ethanol mandate is held at the 15 billion gallons cap. As for biodiesel, our working assumption is that this is the marginal biofuel to meet the advanced biofuel mandate, and so the extrapolation as to its level is not required for the model that we discuss next (the biodiesel mandate, *per se*, is not binding).[4] The last column of table 1 constitutes the "2022 scenario" that is analyzed in our counterfactual simulations, along with a few other scenarios discussed below.

The Model

The model consists of the following parts: US supply for corn and soybeans, consistent with equilibrium conditions in the land market; US oil supply; transformation sectors that produce ethanol and biodiesel from agricultural crops, and gasoline and diesel from domestic and imported crude oil; imports of crude oil and exports of corn and soybeans (including soybean oil and meal); rest of the world's demands for corn and soybean products imports; US demand for food products, transportation fuels and other fuels. The model allows for the endogeneity of crude oil, corn and soybean product prices, in addition to representing equilibrium in the US markets for food products and transportations fuels. The equilibrium conditions used to close the model are based on a novel representation of the arbitrage conditions for RIN prices.

Domestic Production

The model represents three domestically produced primary products: corn, soybeans, and crude oil. Concerning the two agricultural outputs, we conceive of their production as arising from an equilibrium allocation of (finite) cropland across three alternatives: corn, soybean, and all other uses. Given the purpose of this analysis, in our model it is important to represent not just the responsiveness of the supply of each product of interest to changes in its own price, but also the substitutability between corn and soybean, i.e., the cross-price effects. Consistent with recent work addressing agricultural supply response to price changes induced by the biofuel expansion (e.g., Hendricks et al. 2014, Berry 2011), we postulate both a land allocation response and a yield response. Consequently, the supply functions for corn and soybeans are represented as:

(1) $S_i(p_i, p_j) = y_i(p_i)L_i(p_i, p_j), \quad i, j = c, s$ and $i \neq j$

where p denotes prices and the subscripts c and s indicate corn and soybeans, respectively. Hence, the yield functions $y_i(p_i)$ are presumed to respond to own price only, whereas the acreage allocation functions $L_i(p_i, p_j)$ depend on both corn and soybean prices (which are endogenously determined in the model). Provided the symmetry condition $\partial S_c / \partial p_s = \partial S_s / \partial p_c$ holds, the supply functions $S_c(p_c, p_s)$ and $S_s(p_c, p_s)$ are integrable into an aggregate profit function $\Pi(p_c, p_s)$ and thus satisfy $S_c = \partial \Pi / \partial p_c$ and $S_s = \partial \Pi / \partial p_s$ (by Hotelling's lemma).

As noted, the acreage functions $L_i(p_i, p_j)$ are meant to represent an equilibrium allocation of cropland to three alternatives, but we specify them as depending only on the prices of corn and soybeans. Two rationalizations can be invoked for this procedure: the price of the outside option (other uses) is constant; or, these functions should be interpreted as *mutatis mutandi* supply relationships (i.e., allowing for equilibrium response in the markets for products other than corn and soybeans). Computation of the producer surplus, as done in this article, is possible for either rationalization, although the interpretation of such measure might differ in subtle ways (Thurman 1991). In any case, the price of inputs other than land are held constant (across scenarios), except for energy inputs (because the model will solve for different equilibrium fuel prices across scenarios). Still, under the ancillary simplifying condition that energy inputs are used in fixed proportion with land,[5] it follows that the supply functions of interest can in fact be represented simply as depending on the prices of the two commodities (corn and soybeans). The supply of the other domestically produced primary product, crude oil, is written as $S_R(p_R)$.

Transformation sectors. The refining of crude oil yields gasoline x_g, diesel x_d, and other refined petroleum products x_h. We assume a Leontief (fixed proportions) production technology:

(2) $$x_g = \beta_g Min\left\{ x_R, z_g \right\}$$

(3) $$x_d = \beta_d x_g \big/ \beta_g$$

(4) $$x_h = \beta_h x_g \big/ \beta_g$$

where $x_R \equiv S_R + \overline{S}_R$ is the total supply of crude oil to the US market ($\overline{S}_R$ denotes US imports of crude oil), and z_g represents other inputs used in the refining process.

Domestically produced corn has three uses in the model: it can be exported; it can be transformed into ethanol; and it can meet domestic demand for all other uses (e.g., animal feed). Corn-based ethanol production x_e is represented by the following Leontief production functions:

(5) $$x_e = \alpha_e Min\left\{ \tilde{x}_c, z_e \right\}$$

where $\tilde{x}_c$ is the quantity of corn, and z_e denotes all other inputs, used in ethanol production. We note at this juncture that the model will allow for byproducts—such as distilled dried grains with soluble—that can be valuable as animal feed (Hoffman and Baker 2011). The endogenously determined animal feed products in our model are corn and soybean meal. To account for the feedback effects on these markets of varying ethanol production (across scenarios), the quantities of byproducts which substitute for corn and soybean meal used in livestock feed are represented as $\delta_1 \tilde{x}_c$ and $\delta_2 \tilde{x}_c$, respectively.

Similarly, domestically produced soybeans have two uses: they can be exported as beans; or, they can be crushed to produce oil and meal. In turn, some of the meal and oil that is domestically produced by the crushing process is exported. Given the constant returns to scale technology in the crushing process, and assuming that there are no particular comparative advantages in this process, without loss of generality we can simplify the model and assume that each bushel of soybeans that is exported is really a fixed-proportion bundle of soybean oil and meal.[6] Hence, we presume that the entire domestic production of soybeans is converted into soybean oil x_v and meal x_m by the following Leontief technology:

$$x_v = \alpha_v Min\{S_s, z_v\} \tag{6}$$

$$x_m = \alpha_m x_v / \alpha_v \tag{7}$$

where S_s is domestic soybean supply, and z_v denotes other variable inputs used in the production of vegetable (soybean) oil. Next, soybean oil can be exported, it can be converted into biodiesel, or it can meet domestic demand for all other uses. Conversion of soybean oil into biodiesel x_b takes place according to this Leontief technology:

$$x_b = \alpha_b Min\{\tilde{x}_v, z_b\} \tag{8}$$

where $\tilde{x}_v$ is quantity of soybean oil, and z_b denotes all other variable inputs, used in the production of biodiesel.

Demand

For the analysis of various scenarios, the model endogenizes both agricultural product prices and fuel prices. We explicitly model the demand for transportation fuels (gasoline and diesel), as well as the demand for other energy products produced by refining crude oil. Because transportation fuels in our model blend fossil and renewable fuels, it is important to account for their energy content. Our maintained assumption is that consumers ultimately care about miles traveled (de Gorter and Just 2010). Having accounted for their different energy contents, ethanol is considered a perfect substitute for gasoline and biodiesel a perfect substitute for diesel. To permit an internally consistent welfare evaluation of alternative policy scenarios, domestic demand functions are obtained from a quasi-linear utility function for the representative consumer, which is written as:

$$U = I + \Phi(p_{gf}, p_{df}) + \Psi(p_h) + \Theta(p_c, p_m, p_v) - \Lambda(E) \tag{9}$$

where I denotes monetary income which, along with all prices, is expressed in terms of a numeraire good whose price is normalized to one. Subscripts *gf* and *df* here denote gasoline fuel and diesel fuels, respectively (i.e., blends of fossil and renewable fuels). Thus, we are postulating additive separability between transportation fuels, heating oil, and food/feed products. This property assumes that a number of cross-price elasticities are equal to zero. But some critical substitution relations (between food/feed products, and between various fuels) are modeled explicitly. Note also that these preferences include the externality cost of transportation fuel consumption via the term $\Lambda(E)$, where E denotes total world GHG emissions associated with the consumption vector of all energy products (accounting for the fact that biorenewable energy products entail savings on emission).

The foregoing approach of modeling biofuels and fossil fuels as perfect substitutes, once expressed in equivalent energy units, is consistent with other recent studies (e.g., Holland et al. 2015), but some additional discussion may be warranted vis-à-vis the “blend wall” issue. The latter refers to the maximum amount of ethanol that can be sold via the so-called E10 gasoline blend (which contains a maximum of 10% ethanol). As noted by Stock (2015, p. 13) “…this is more accurately not a ‘wall’ but rather a situation in which additional ethanol must be provided through higher blends.” When that is the case, it may be important to represent separately consumers’ demand for E10 and E85, the higher-ethanol blend that can be used by flexible fuel vehicles (FFVs) (Anderson 2012, Salvo and Huse 2013). As discussed in more detail below, feasibility of the RFS mandate is not an issue in the benchmark 2015 year, nor for the 2022 scenario. Feasibility may be an issue for the higher ethanol levels of the optimal mandates that we calculate, in which case the putative welfare gains of optimal mandates need to be properly qualified.

Demand functions for corn, soybean oil and soybean meal are written as $D_c(p_c, p_m, p_v)$, $D_v(p_c, p_m, p_v)$, and $D_m(p_c, p_m, p_v)$, respectively, and satisfy $D_c = -\partial\Theta/\partial p_c$, $D_v = -\partial\Theta/\partial p_v$ and $D_m = -\partial\Theta/\partial p_m$. Similarly, domestic demand functions for blended gasoline fuel and blended diesel fuel, $D_{gf}(p_{gf}, p_{df})$ and $D_{df}(p_{gf}, p_{df})$, satisfy $D_{gf} = -\partial\Phi/\partial p_{gf}$ and $D_{df} = -\partial\Phi/\partial p_{df}$. Again, in principle the specification can handle some substitution possibility between gasoline and diesel. Such a possible substitution is however not maintained for non-transportation petroleum products, the demand for which is $D_h(p_h) = -\partial\Psi/\partial p_h$. The actual parameterization of these demand functions will assume a quadratic structure for the functions $\Phi(\cdot)$, $\Psi(\cdot)$ and $\Theta(\cdot)$, such that the implied demands are linear. Demand functions for agricultural products exported to the rest of the world (ROW), written as $\bar{D}_c(p_c)$, $\bar{D}_v(p_v)$ and $\bar{D}_m(p_m)$, are also assumed to be linear. As for the externality cost $\Lambda(\cdot)$, we will assume that the social cost is linear in total carbon emission.

Equilibrium

The equilibrium conditions represent the situation where the United States is a net importer of crude oil, a net exporter of corn, and a net exporter of soybean oil and meal (as noted earlier, exports of soybeans *per se* are treated as exports of soybean oil and meal). These trade flows are endogenously determined by the equilibrium conditions that solve for the equilibrium prices. To exactly match the data of the benchmark 2015 year, all other trade flows (because they are of minor importance) are treated as exogenous. Similarly, our equilibrium conditions reflect observed stock changes in the benchmark year, although these quantities are treated as exogenous across scenarios.

It is useful to separate the equilibrium conditions that apply in any one scenario into market clearing conditions and arbitrage conditions. The latter arise from the competitive (zero profit) conditions that apply to the transformation sectors (oil refining, soybean crushing and ethanol production), together with the presumed Leontief production functions. Arbitrage conditions also arise because of policy interventions in the biofuel market, as discussed below. Unlike Cui et al. (2011), none of our scenarios considers the possibility of using border measures (i.e., tariffs). Hence, the arbitrage conditions that link domestic and foreign prices are directly maintained in our model. Which market equilibrium conditions apply, however, does depend on which policy tools (e.g., mandates, taxes, subsidies) are in place. Here we present the equilibrium conditions for the case with binding mandates (the *status quo*).

The statutory mandate levels are: x_{rf}^M for the overall mandate for renewable fuel, x_a^M for the advanced biofuel mandate, x_b^M for the biodiesel mandate, and x_{ce}^M for the cellulosic biofuel mandate (following the RFS convention, all of these mandates, except x_b^M, are measured in ethanol units).[7] These mandates define a hierarchical structure: cellulosic biofuels and biodiesel can be also used to meet the advanced biofuel mandate; and all biofuels can be used to meet the overall renewable fuel mandate (Schnepf and Yacobucci 2013). Consistent with the 2015 benchmark year used to calibrate the *status quo*, there are three binding mandates: x_{rf}^M, x_a^M and x_{ce}^M. Specifically, the binding cellulosic biofuel mandate is met with domestic production, which is exogenous to our model. The advanced biofuel mandate is met by imports of sugarcane ethanol, the quantity of which is exogenous, and biodiesel, either domestically produced or imported (domestic biodiesel produced from feedstock other than vegetable oil, and the imported amount of biodiesel, are treated as exogenous). More specifically, the equilibrium conditions that we characterize below pertain to the case where the quantity of biodiesel exceeds that required to meet the biodiesel mandate, i.e., the "marginal" fuel to meet the advanced biofuel mandate is biodiesel. Hence, the biodiesel mandate, *per se*, is not binding. Finally, the presumption is that the marginal biofuel for the total renewable mandate is corn ethanol (recall that there is no specific corn ethanol mandate *per se*).

The market clearing conditions can now be stated as follows:

$$S_c(p_c, p_s) - \Delta_c = D_c(p_c, p_m, p_v) + \bar{D}_c(p_c) + (1-\delta_1)\frac{x_e}{\alpha_e} \tag{10}$$

$$\alpha_m\left[S_s(p_c, p_s) - \Delta_s\right] - \Delta_m = D_m(p_c, p_m, p_v) + \bar{D}_m(p_m) - \delta_2\frac{x_e}{\alpha_e} \tag{11}$$

$$\alpha_v\left[S_s(p_c, p_s) - \Delta_s\right] - \Delta_v = D_v(p_c, p_m, p_v) + \bar{D}_v(p_v) + \frac{x_b}{\alpha_b} \tag{12}$$

$$x_g - X_g + \zeta_e\left(x_e - X_e + \mu_{ce}x_{ce}^M + M_{se}\right) = D_{gf}(p_{gf}, p_{df}) \tag{13}$$

$$x_d - X_d + \zeta_b\left(x_b + M_b + N_b\right) = D_{df}(p_{gf}, p_{df}) \tag{14}$$

$$x_h - X_h = D_h(p_h) \tag{15}$$

Equation (10) represents equilibrium in the corn market. The term Δ_c here represents change in year-ending (carryover) stocks. The last term on the right-hand-side (RHS) of equation (10) represents the net amount of corn devoted to the production of ethanol, where the coefficient $(1-\delta_1)$ accounts for the quantity of byproducts from ethanol production that substitute for corn as livestock feed. Equation (11) represents equilibrium in the soybean meal market. In this equation, the terms Δ_s and Δ_m represent variations in stocks for soybeans and soybean meal, respectively, whereas the term $\delta_2 x_e/\alpha_e$ accounts for the quantity of ethanol production byproducts that substitute for soybean meal as animal feed. Equation (12) represents equilibrium in the soybean oil market. In this equation, the term Δ_v represents change in stocks of soybean oil. The last term on the RHS of equation (12) represents the amount of soybean oil that is processed into biodiesel. Equation (13) represents equilibrium in the gasoline fuel market, where X_g denotes exports of unblended gasoline. Note that ethanol from all origins—domestically produced corn-based ethanol x_e, net of export X_e and imports of sugarcane ethanol M_{se}, as well as domestically produced cellulosic ethanol—is blended with gasoline, with everything expressed in gasoline energy equivalent units via the coefficient ζ_e. Because only a very small portion of the cellulosic biofuel mandate is met with cellulosic ethanol, however, only the latter amount (denoted $\mu_{ce}x_{ce}^{M}$) is presumed blended with transportation fuel.[8] Equation (14) represents equilibrium in the diesel fuel market. Here X_d represents exports of refined diesel, M_b represents imports of biodiesel and N_b represents biodiesel domestically produced with feedstock other than vegetable oil. Finally, equation (15) represents equilibrium in the market for the composite third product of refining crude oil.

The quantity of corn ethanol and biodiesel in these market clearing conditions must be consistent with the binding mandates, that is, the following identities will hold at the equilibrium:

(16) $$x_e \equiv x_{rf}^{M} - x_{a}^{M} + X_e$$

(17) $$x_b \equiv \left(x_a^M - x_{ce}^M - M_{se} \right) / \vartheta - M_b - N_b$$

where ϑ is the coefficient that, as per the RFS regulation, converts biodiesel quantities into ethanol units ($\vartheta = 1.5$ for traditional biodiesel). The quantities of petroleum products in these market clearing conditions, on the other hand, must satisfy the postulated production relationships, where the total supply of crude oil to the US refining sector depends on the oil price:

(18) $$x_g \equiv \beta_g \left[S_R(p_R) + \bar{S}_R(p_R) \right]$$

(19) $$x_d \equiv \beta_d \left[S_R(p_R) + \bar{S}_R(p_R) \right]$$

(20) $$x_h \equiv \beta_h \left[S_R(p_R) + \bar{S}_R(p_R) \right]$$

In equilibrium, prices must also satisfy arbitrage relations that reflect the zero-profit conditions implied by competitive equilibrium in constant-returns to scale industries. Specifically:

(21) $$\alpha_v p_v + \alpha_m p_m = p_s + w_v$$

(22) $$\alpha_e p_e + \delta_2 p_m = p_c \left(1 - \delta_1\right) + w_e$$

(23) $$\alpha_b p_b = p_v + w_b$$

(24) $$\beta_g p_g + \beta_d p_d + \beta_h p_h = p_R + w_g$$

Equation (21) represents the zero profit in soybean crushing (the value of all outputs equal the cost of all inputs). Similarly, equations (22), (23) and (24) represent the zero profit conditions in ethanol production, bio-diesel production and crude oil refining, respectively.

Finally, to close the model, the prices of blended fuels p_{gf} and p_{df} need to be linked to the prices of endogenous fossil fuel inputs (gasoline and diesel) and the prices of endogenous renewable fuels (ethanol and biodiesel). These relationships need to reflect the fact that gasoline and diesel blends are subject to federal and state motor fuel taxes (represented by the per-unit terms t_{gf} and t_{df}), and that biodiesel enjoys a per-unit blending subsidy ℓ_b. More importantly, these arbitrage relationships must reflect the cost that obligated parties (refiners and blenders) face for complying with the binding mandates, which are mediated by RIN prices.

RIN Prices and Arbitrage/Zero Profit Conditions

Our model is specified in terms of absolute mandate quantities, consistent with the RFS statutory requirements laid out in the EISA legislation. As noted earlier, however, the implementation of these RFS mandates takes the form of "fractional requirements" (determined annually by the EPA) imposed on obligated parties (e.g., importers and refiners). These fractional requirements define how much of each renewable fuel must be blended in the fuel supply for each gallon of refined fossil fuel that is marketed. Obligated parties can meet their RVOs by purchasing renewable fuel themselves, or can show that others have done so by purchasing RINs. In fact, because obligated parties are typically not those who produce and/or blend biofuels in the fuel supply, an active market for RINs has emerged, and the associated RIN prices data can prove useful for empirical analyses (Knittel, Meiselman and Stock 2015, Lade, Lin Lawell and Smith 2016). The purpose of this section is to show explicitly that this, somewhat intricate, RFS enforcement mechanism can be fully rationalized in the context of a model, such as ours, that is specified in terms of absolute mandates.

Let R_{rf}, R_a, R_b and R_{ce} denote the RIN prices for generic renewable fuel (e.g., corn-based ethanol), advanced biofuel, biodiesel and cellulosic biofuel, respectively. The nested nature of the RFS mandates imply that $R_{ce} \geq R_a \geq R_{rf}$, and also that $R_b \geq R_a \geq R_{rf}$. Our working assumption that soybean-oil-based biodiesel is the marginal fuel for the purpose of meeting the advanced biofuel mandate implies that the RIN price of advanced biofuels is equal to that of biodiesel, $R_a = R_b$. Furthermore, the presumption that the marginal biofuel for the total renewable mandate is corn ethanol means that R_{rf} is effectively the RIN price for corn-based ethanol. Next, let the fractional requirements that obligated parties are required to meet for total renewable fuel, advanced biofuel and cellulosic biofuel be represented, respectively, by s_{rf}, s_a and s_{ce}. Then, given the foregoing assumptions on the marginal fuels, it follows that the implicit RFS requirement for corn-based ethanol is $\hat{s}_e = s_{rf} - s_a$, and the implicit RFS standard for biodiesel $\hat{s}_b = s_a - s_{ce}$.

To close the model using the arbitrage conditions from RIN prices, we interpret the latter as representing what has been termed as the "core value" of RINs (McPhail, Westcott and Lutman 2011). In particular, we abstract from the fact that obligated parties can borrow RINs from the next year and/or they can save RINs to be used next year (Lade, Lin Lawell and Smith 2016). These core RIN prices are derived as follows. Given that consumer demand is represented in energy units, a blender can choose to sell one unit of pure ethanol as gasoline fuel and earn $\zeta_e p_{gf}$, upon incurring the motor fuel tax cost t_{gf}. Because the RFS envisions obligations only when using fossil fuels, this strategy does not require the seller to turn in RINs. Hence, the blender would be free to sell the RIN that is "separated" when the unit of ethanol is sold as fuel. The minimum price this agent would accept, at given prices, for one generic renewable fuel RIN therefore is:

(25) $$R_{rf} = p_e + t_{gf} - \zeta_e p_{gf}$$

Analogously, a blender selling one unit of biodiesel can earn $\zeta_b p_{df}$ upon incurring the motor fuel tax cost t_{df}. This strategy would separate ϑ RINs. The minimum price this agent would accept, at given prices, for one biodiesel RIN therefore is:

(26) $$R_b = \frac{p_b - \ell_b + t_{df} - \zeta_b p_{df}}{\vartheta}$$

To make the foregoing operational for the purpose of closing the model, next we consider the demand side for RINs. The zero profit conditions for an obligated party who sells only fossil-based gasoline and/or diesel, and buys all needed RINs, are:

(27) $$p_{gf} - p_g - t_{gf} = \hat{s}_e R_{rf} + \hat{s}_b R_b + s_{ce} R_{ce}$$

(28) $$p_{df} - p_d - t_{df} = \hat{s}_e R_{rf} + \hat{s}_b R_b + s_{ce} R_{ce}$$

These two conditions can be combined to provide the zero-profit condition that must apply to the overall refining/blending industry which, as in Lapan and Moschini (2012), is assumed to be competitive and operating under constant returns to scale. To this end, we need to express the RFS fractional requirements s_i in terms of mandated quantities. Assuming binding mandates x_{rf}^M, x_{ce}^M and x_a^M, and exogenously given trade flows (recall: fossil fuel exports are not subject to the fractional RFS requirement), then

(29) $$s_{ce} = \frac{x_{ce}^M}{x_g + x_d - (X_g + X_d)}$$

(30) $$\hat{s}_e = \frac{x_{rf}^M - x_a^M}{x_g + x_d - (X_g + X_d)}$$

(31) $$\hat{s}_b = \frac{x_a^M - x_{ce}^M}{x_g + x_d - (X_g + X_d)}$$

Using equations (25)-(31), the zero-profit condition for the integrated refining-blending industry can then be written as:

(32) $$\begin{aligned}(p_{gf} - t_{gf} - p_g)(x_g - X_g) + (p_{df} - t_{df} - p_d)(x_d - X_d) = (p_e + t_{gf} - \zeta_e p_{gf})(x_e - X_e) \\ + (p_b - \ell_b + t_{df} - \zeta_b p_{df})(x_b + M_b + N_b) + \frac{M_{se}}{\vartheta}\left(p_b - \ell_b + t_{df} - \zeta_b p_{df}\right) + x_{ce}^M R_{ce}\end{aligned}$$

The two terms on the LHS of equation (32) can be interpreted as the industry profit from selling fossil gasoline and fossil diesel, respectively. This profit balances the net industry cost of having to meet the (binding) mandates. Specifically, the first term on the RHS of (32) represents the net loss from selling $(x_e - X_e)$ units of corn-based ethanol; note that the motor fuel tax is levied on the volume of ethanol sold, whereas the revenue portion adjusts the price of (blended) gasoline fuel by the energy content of ethanol. The second term on the RHS represents the net loss from selling $(x_b + M_b + N_b)$ units of biodiesel; in addition to the role of the motor fuel tax and energy content, similar to the case of corn-based ethanol, this term also accounts for the biodiesel blending subsidy. The third term on the RHS represents the cost of marketing the (exogenous amount of) sugarcane ethanol M_{se}. Because this ethanol contributes to meeting the advanced biofuel mandate, and because the marginal fuel for meeting this mandate is biodiesel, then the implicit compliance costs associated with sugarcane ethanol is given by the core value of biodiesel RINs. Finally, the last term of the RHS represents the cost of complying with the cellulosic biofuel mandate (both the quantity mandate x_{ce}^M and the corresponding RIN price R_{ce} are exogenous to the model).

Because the model endogenously determines two renewable fuel prices—corn ethanol and biodiesel—the zero-profit condition for the integrated refining-blending industry in equation (32) is not sufficient to close the model (unlike in Cui et al. 2011, for instance). The additional price arbitrage condition is derived by combining equations (27) and (28):

(33) $$p_{gf} - p_g - t_{gf} = p_{df} - p_d - t_{df}$$

This equilibrium price relation embeds a critical implication of the RFS: marketing a gallon of fossil gasoline entails the same compliance cost as marketing a gallon of fossil diesel (i.e., the RHS terms of (27) and (28) are the same). In conclusion, therefore, the equilibrium conditions are given by equations (10)-(24), along with equations (32) and (33). These 17 equations are solved for 17 endogenous variables: p_c, p_s, p_m, p_v, p_R, p_{gf}, p_{df}, p_g, p_d, p_h, p_e, p_b, x_e, x_b, x_g, x_d and x_h.

Equilibrium Conditions for Other Scenarios

Equilibrium conditions for scenarios other than the *status quo* will need to be appropriately adjusted. For example, without binding mandates and with no biodiesel subsidy, the equilibrium conditions would not require the arbitrage relations (32) and (33). Instead, the required arbitrage relations (for an interior solution) would be

(34) $p_g = p_{gf} - t_{gf}$

(35) $p_d = p_{df} - t_{df}$

(36) $p_e = \zeta_e p_{gf} - t_{gf}$

(37) $p_b = \zeta_b p_{df} - t_{df}$

The set of equilibrium conditions for this case would then be given by equations (10)-(15), equations (18)-(24), and equations (34)-(37). These conditions also characterize the *laissez faire* scenario, provided that $t_{gf} = t_{df} = 0$. The supplementary appendix online shows how the equilibrium conditions for the case of no RFS mandates can be adjusted to maintain the assumption that some ethanol is likely to be required, even without RFS mandates, as an oxygenate for gasoline fuel to meet desired octane levels (a scenario that we explicitly consider in the policy evaluation section).

Parameterization

The parameters of the model are calibrated to represent the most recent available consistent benchmark data set (the year 2015), in order to capture current conditions in agricultural and energy markets. Specifically, the data for crop variables are based on the 2014/2015 marketing year, whereas crude oil and fuel variables (fossil and renewable) are based on calendar year 2015.[9] The purpose of calibration is to choose parameter values for the functional forms of demand and supply so that: (a) the equilibrium conditions using the parameterized functions, along with the observed values of exogenous variables, produce the values of endogenous variables actually observed in the 2015 benchmark year; and, (b) the parameterized functions imply elasticity formulae that, once evaluated at the 2015 benchmark data, match assumed elasticity values. The functions that we parameterize are the domestic supply functions for corn and soybean; the domestic demand functions for corn, soybean meal and soybean oil; the foreign import demand functions for corn, soybean meal and soybean oil; the domestic supply and foreign export supply functions for crude oil; the domestic demand functions for gasoline fuel and diesel fuel; and, the domestic demand function for other refined petroleum products. All of these functions are postulated to be linear.

Table 2 reports the assumed elasticity parameters used to calibrate the model, along with a brief description of sources/explanations. The remaining coefficients used to calibrate the model are reported in tables A1 and A2 in the Appendix.

Elasticities

The elasticity values used to calibrate the model, summarized in table 2, are based on the literature, whenever possible, or assumed to reflect consensus on their qualitative attributes. A full discussion of sources and elasticity derivations is included in the supplementary appendix online. A crucial set of parameters, given the objective of the study, concerns the own and cross-price supply elasticities for corn and soybeans. Given the postulated structure discussed earlier, such elasticities reflect both acreage allocation decisions as well as yield response effects: $\eta_{ii} = \eta_{ii}^{L} + \eta_{ii}^{y}$ $(i = c, s)$ and $\eta_{ij} = \eta_{ij}^{L}$ ($i = c, s, i \neq j$). For acreage elasticities Hendricks, Smith and Sumner (2014) provide a useful benchmark. Consistent with previous work, they find an inelastic response for both corn and soybeans, and also a relatively large cross-price elasticity. As we show in the supplementary appendix online, this means that the implied elasticity of land allocated to these two crops, when both corn and soybean prices are scaled together, is almost completely inelastic. As noted by the AJAE editor, these elasticities may not be representative of the country as a whole because they are based on data from only three states of the central corn belt (where most of the cropland is already allocated to these two crops). To proceed, we have estimated an acreage response model based on national data for the period 1970-2015 (see the supplementary appendix online for details). The estimates we obtain imply a somewhat more elastic acreage response than the long run estimates of Hendricks, Smith and Sumner (2014), and these are the values in table 2 used to calibrate the model. As for yield elasticities, Berry (2011) provides an extensive review of existing empirical evidence. The broad consensus is that virtually all of the crop supply response comes from acreage response, not from yield response. Here we use a set of point estimates for yield response to price from Berry and Schlenker (2011).

The own-price elasticity of domestic corn demand is the same as used by de Gorter and Just (2009) and Cui et al. (2011), and similar values are assumed for soybean oil and meal demands. Cross-price demand elasticities are calculated based on these own-price elasticities and one additional parameter that restrict all of the Allen-Uzawa elasticities of substitution to be the same. Import elasticities for the rest of the world (ROW) notionally reflect both ROW demand and supply responses. To keep the model tractable, we do not explicitly model such underlying functions, nor do we represent cross-price effects. But in the supplementary appendix online we develop the structural relations between demand and supply elasticities and the import demand elasticity, and use such relations to guide the choice of our baseline import elasticity values. For soybean products, our baseline elasticities are broadly consistent with those reported by Piggott and Wohlgenant (2002), whereas for corn our ROW import demand is more elastic than that postulated by Cui et al. (2011).

Another crucial set of elasticities relates to fuel markets. A considerable body of literature, succinctly reviewed in Difiglio (2014) and Greene and Liu (2015), has documented that gasoline demand is very inelastic. Indeed, Hughes, Knittel and Sperling (2008) find that it has become more inelastic in recent years. We conservatively assume the elasticity of gasoline demand estimated by Bento et al. (2008), who use a microeconomic model that allows consumers to respond to price changes with both car choice and miles traveled. This value is also close to the estimate obtained, with a completely different methodology, by Coglianese et al. (2017), and actually more elastic than other recent estimates (e.g., Lin and Prince 2013). Consistent with findings in the literature (Dahl 2012, Winebrake et al. 2015) we postulate that the demand for diesel fuel is more inelastic than that for gasoline fuel, while the demand for other refined fuel products is specified as relatively more elastic. Similar to demand elasticities, the consensus is that the crude oil supply is very inelastic (Difiglio 2014, Greene and Liu 2015). Our baseline parameterization relies on the crude oil supply elasticity used by the US EIA National Energy Modeling System (EIA 2014). As for the ROW export supply of crude oil to the United States, again this reflects both ROW supply and demand responses. Concerning the latter, for the United States our model presumes elasticities of demand for refined products, not crude oil. But using the structural (Leontief) production relations between refined products and crude oil, and the equilibrium arbitrage relation between prices in (24), the supplementary appendix online shows that, for the 2015 calibration year, the implied US crude oil demand elasticity is -0.20. If the ROW has a similar demand elasticity, and its crude oil supply elasticity is the same as in the United States, as assumed in EIA (2014), then we can obtain the ROW export supply elasticity value reported in table 2.

Technical Coefficients

The full set of technical coefficients is reported in table A1 in the Appendix. For ethanol, we assume that one bushel of corn yields 2.8 gallons of ethanol, just as in Cui et al. (2011). What we do differently in this article is provide a more careful account of the byproducts from ethanol production. In particular, we recognize that a variety of such byproducts may be produced, and that their use as animal feed substitutes for both corn and soybean meal (Mumm et al., 2014). This is important in our context, because the quantities and prices of both corn and soybean meal are endogenous in the model. Mumm et al. (2014) conclude that byproducts of ethanol production return 30.7% (in weight) of the corn used as feed equivalent, with 71% of these byproducts replacing corn in animal feed, and the remaining 29% replacing soybean meal. Our calibrated parameters δ_1 and δ_2 maintain these proportions, while adjusting to the units used (bushels for corn and short tons for soybean meal). Production of biodiesel is assumed to require 7.65 pounds of soybean oil per gallon of biodiesel (EIA), and we ignore the byproducts for this process (which have limited value, compared with those arising from ethanol production). The Leontief coefficients for the production of soybean oil and meal by crushing soybeans are obtained from the actual 2015 data for the soybean complex, which shows that 1,873 million bushels of soybeans produced 45.1 million short tons of soybean meal and 21,399 million pounds of soybean oil.

Finally, to represent blended fuels in coherent energy units, for the purpose of modeling demand, the British Thermal Unit (BTU) conversion factors of the various fuels are used (EIA). By using the coefficients ζ_i thus obtained, we are able to express blended gasoline fuel in gasoline energy-equivalent gallon (GEEG) units, as in Cui et al. (2011). By a similar procedure, blended diesel fuel is expressed in diesel energy-equivalent gallon (DEEG) units, and other refined petroleum products are expressed in kerosene energy-equivalent gallon (KEEG) units.

GHG Emissions and Social Cost

Total GHG emission relevant for assessing the alternative biofuel policies scenarios include those associated with US consumption of transportation fuel and other refined petroleum products. But, because we are dealing with a global externality, it is important to account for the induced change in ROW emission induced by the RFS (the so-called leakage effect). Hence, total emission is computed as $E = \sum_j q_j E_j + \bar{D}_R E_R$, where q_j denotes the quantity of individual fuel types consumed in the United States, E_j denotes the corresponding emission rate, $\bar{D}_R$ is the ROW crude oil consumption, and E_R is the associated emission rate. These (lifecycle) emission rates, measured as kg/gallon of carbon dioxide equivalent (CO_2e) and reported in table A2 in the Appendix, are taken from EPA (2010) and reflect consensus estimates of GHG emission savings provided by biofuels.[10] As for GHG emissions rate of other refined petroleum products, the coefficient we computed is based on five major products of this category.[11]

To translate GHG emission into a social cost, we assume a constant marginal social damage of pollution, and thus write $\Lambda(E) = \gamma E$. Regarding γ, the marginal social cost of carbon dioxide emissions, the large body of existing work has produced a bewildering array of estimates (Tol 2009), a reflection of the conceptual and practical complexities of such an endeavor. In addition to the familiar difficulties of choosing the baseline value for this parameter, we also need to address the question of what we intend to measure. Our model is predicated on a US-centered welfare criterion. For internal consistency, therefore, our model suggests that only the carbon-emission implications of US biofuel policies for the US economy are relevant. Hence, we follow Cui et al. (2011), who rationalize the use of a benchmark global social cost of \$80/ tCO_2, based on the *Stern Review* (Stern 2007), and then apportion this cost based on the share of US share of the world economy to obtain the adopted value of $\gamma = \$20/$ tCO_2.[12]

Other Baseline Variables

Data on prices and quantities used to calibrate the model are reported in the supplementary appendix online, which includes sources and calculation methods. Many of these values are also reported in the *status quo* column of table 3 below (given that parameters were correctly calibrated, simulation of the *status quo* reproduces the benchmark variables). For most variables, the data pertains to observed representative values for the benchmark (2015) year, but for some variables the benchmark values are calculated to be consistent with the model. These include gasoline fuel and diesel fuel prices, of course. Also, the reported values for the net export of soybean meal and soybean oil are the sum of actual net exports and implied net exports from the export of soybeans (as discussed earlier). The price of biodiesel is also calculated. It turns out that a representative biodiesel price, such as that reported by the USDA,[13] would imply an unreasonably low "core value" for the corresponding RIN price, if one assumed that the biodiesel blending subsidy was fully expected, as maintained in equation (26). But in fact this subsidy was passed into law only on December 18, 2015, although it retroactively applied to the entire 2015 calendar year. The considerable uncertainty surrounding the availability of the biodiesel blending subsidy throughout

2015, as well as contractual arrangements that many market operators put in place to deal with that (Irwin 2015), suggests that it is unwise to use the observed biodiesel price in the context of a model that presumes the certainty of such a subsidy. Therefore, we elected to compute the biodiesel price that would be implied by the observed 2015 RIN prices.[14]

Other variables of interest reported in the *status quo* column of table 3 also include motor fuel taxes and RIN prices. Concerning motor fuel taxes, we note at this juncture that these taxes, in virtually all cases, are levied on volume basis (Schroeder, 2015), a feature that we have maintained in our structural model. For gasoline, the assumed per-unit tax is the sum of the federal tax (¢18.40/gallon) and a weighted average of state taxes (¢26.49/gallon). For diesel, the assumed per-unit tax is the sum of the federal tax (¢24.40/gallon) and a weighted average of state taxes (¢27.24/gallon). The RIN price for ethanol is the 2015 average of D6 RIN prices, whereas for biodiesel it is the average of the 2015 annual averages of D4 and D5 RIN prices ($0.7475 and $0.707, respectively), all from OPIS data.[15]

Market and Welfare Impacts of the RFS: Alternative Scenarios

The model outlined in the foregoing sections is used to evaluate a number of policy scenarios, specifically: 2015 RFS mandate levels (the *status quo*); implementation of the 2022 RFS mandates, with projected adjustments for cellulosic biofuels as discussed in section 2 (table 1); and, repeal of biofuel mandate policies (No RFS).[16] In addition to evaluating the above scenarios, because we have an explicit welfare function, the model permits us to characterize optimal biofuel mandates (a second best policy, in this setting), for both biodiesel and corn-based ethanol. Finally, for the purpose of benchmarking the welfare implications of these policies, we also evaluate the *laissez faire* scenario (i.e., no biofuel policies and no taxes on transportation fuels).

For each of these five scenarios the model permits computation of market effects (e.g., prices and equilibrium quantities), as well as an assessment of the welfare impacts. Because of its structure, the model accounts for potential welfare gains accruing to the United States through the impact that alternative biofuel policies can have on the US terms of trade for oil, corn and soybean products. Our welfare calculations also identify important distributional effects by breaking down welfare changes for individual components. We specifically identify net benefits accruing to US consumers, measured as consumer surplus from the integrable system of demand equations derived from the indirect utility function in equation (9); net benefits accruing to the domestic agricultural sector (with aggregate producer surplus consistently calculated as discussed in the supplementary appendix online); net benefits accruing to domestic producers of crude oil; net government tax revenue; and, the monetary value of GHG emission savings.

Results

In table 3 and table 4, results pertaining to the various scenarios are reported by column in the following order: *laissez faire*, no RFS, 2015 mandates, projected 2022 mandates, and optimal mandates. The top portion of table 3 reports the value of the active policy variables for each scenario. Note that, with the exception of the *laissez faire*, all scenarios envision motor fuel taxes at the baseline level. In addition to the relevant mandates, the *status quo* also includes the \$1/gallon biodiesel subsidy (technically, a tax credit). This subsidy is omitted from the optimal mandates and 2022 scenarios (this is without loss of generality, because the biodiesel mandate is binding in those scenarios). Next, table 3 reports the equilibrium prices and quantities for all scenarios that are considered. Whereas table 3 focuses on the market impact of policies in the various scenarios, table 4 pertains to the computed welfare impacts, which are reported as changes from the "No RFS" scenarios, i.e., the *status quo* before biofuel policies. The estimated aggregate welfare effects are decomposed into several subcomponents to describe the distributional impacts of RFS policies (including on domestic agricultural producers, domestic crude oil producers, and consumers). The impacts on consumer surplus in transportation fuel demand is decomposed into changes accruing via gasoline fuel demand and diesel fuel demand (this decomposition is feasible due to the zero substitution possibilities between the two fuel demands).

One of the welfare components in table 4 is the monetary value of the policies' impact on changes in GHG emissions. These emission changes are also reported separately in physical units (tCO_2e), and decomposed between those occurring in the United States and in the ROW. The latter accounts for the implication of "leakage," which arises when unilateral efforts to reduce a global externality are thwarted by induced emission elsewhere (Hoel 1991). One of the two main avenues for carbon leakage to occur is via the impacts of policies on terms of trade (Felder and Rutherford 1993). Because the model can trace the impact of the RFS on equilibrium crude oil price, we can account for the leakage effect that arises because the ROW oil consumption responds to changes in crude oil price.[17]

Status quo, status quo ante, and laissez faire. Given the calibration strategy described in the foregoing, the values of equilibrium variables for the "2015 mandates" column in table 3 are equal to the 2015 values that were used in calibration, a verification that the intercepts and coefficients of all demand and supply functions are precisely calibrated. The ethanol blending ratio in the calibration data is 9.88%, indicating that the blend wall issue is not a concern in the benchmark year. The "No RFS" scenario, as noted, presumes that all mandates and biodiesel subsidies are repealed. Comparison of this scenario with the "2015 mandates" case provides some insight as to the overall market impacts of the current RFS. The largest impact is on agricultural prices: relative to the *status quo ante* the RFS increases corn price by 34% and the soybean price by 9%. All this notwithstanding the fact that the oxygenate requirement for ethanol (which turns out to bind) entails the use of 4.1 billion gallons of ethanol in the "No RFS" scenario. Because biodiesel biases demand of soybean products, the RFS increases soybean oil price by 49% whereas soybean meal price actually declines (by 3.6%). Not surprisingly, the RSF impact on crude oil price (and refined products prices) is much smaller: the crude oil price is estimated to decline by 1.4%, the gasoline price to decline by 9.5% (the prices of diesel and of other refined petroleum products instead increase—reduced amount of refined crude oil, along with the Leontief technology, result in a relative scarcity of these refined products). The RFS leads to a modest contraction in domestic crude oil production, and a larger decline in imports of crude oil (which drop by about 6%).

The *laissez faire* scenario, in addition to the repeal of the RFS, also envisions dropping all motor fuel taxes. This is not a scenario with realistic policy prospects, of course, but it is of some interest to gain insights into the working of the model. Interestingly, the production of corn-based ethanol in the *laissez faire* is considerably higher than in the "No RFS" scenario (the 3% oxygenate requirement is not binding in *laissez faire*). Correspondingly, the corn price is also considerably higher in the *laissez faire* relative to the "No RFS" scenario. The reason for this effect has to do with the impact of transportation fuel taxes. Consistent with the institutional setup, we have modeled these motor fuel taxes as levied on a volume basis (Schroeder, 2015). And, under the presumption that consumers care about miles traveled, fuel demand accounts for the different energy content of biofuels. Hence, as noted by Cui et al. (2011), motor fuel taxes are inherently biased against fuels (such as biofuels) that have lower energy content than fossil fuels. Conditional on such motor fuel taxes being levied per unit of volume of blended fuel, a subsidy for ethanol (and biodiesel) would actually be required just to level the playing field (vis-à-vis the objectives of a Pigouvian tax).

Turning to the welfare impacts reported in table 4, comparing the 2015 mandates case with the "No RFS" scenario we find that aggregate welfare is improved by biofuel policies, by $2.6 billion. In the logic of the model, there are two distinct reasons why RFS policies may improve welfare: they can help correct the carbon pollution externality (under the maintained presumption that biofuels are less polluting than fossil fuels); and, because the United States is a large country, they may lead to favorable changes in the US terms of trade. It is immediately apparent from table 4 that no portion of the welfare gain associated with 2015 mandates (relative to the no RFS scenario) can be ascribed to a reduction in the carbon externality. The increased use of biofuels does reduce carbon emission in the United States (by about 29 million tCO_2e), but this effect is more than offset by increased ROW emissions caused by the RFS-induced decline in the price of crude oil. Leakage, therefore, turns out to imply that US biofuel policies do not contribute to reducing global emissions. It is important to stress that the effects we are quantifying here are distinct from the indirect land use effects emphasized by other critics of US biofuel policies (e.g., Searchinger et al. 2008). Even abstracting from the latter, we find that leakage via terms of trade effects essentially nullifies the potential environmental gains arising from using (marginally) more environmentally friendly fuels.

When comparing the 2015 mandates with the *status quo ante*, it is apparent that the welfare redistribution effects due to the RFS are large (relative to the overall effects). Agriculture is the big winner. Because of the sizeable increase in the prices of corn and soybeans, noted earlier, the RFS is estimated to increase the sector's producer surplus by $14.1 billion per year. The large increase in land prices that has been observed in recent years (Lence 2014) is certainly consistent with these conclusions. Consumers of gasoline fuel also benefit from the decrease in gasoline price, whereas users of diesel fuels are actually hurt by the RFS (as are the consumers of other refined petroleum products). Overall, therefore, these results suggest that repeal of the RFS would lower domestic welfare, both because of terms of trade effects, and because the resulting excess taxation of biofuels (relative to fossil fuels) would excessively depress biofuel production. It is also of some interest to note that, compared with the no RFS scenario, the *laissez faire* results in higher welfare. This seems counterintuitive, given that the welfare function includes an externality cost, and the *laissez faire* does not have corrective motor fuel taxes. One of the reasons for this outcome is that—given the assumed social cost of carbon—motor fuel taxes are set at a higher level than what would be required to internalize the carbon emission externality.[18]

Year 2022 mandates. The second-to-last column in both table 3 and table 4 considers the 2022 RFS scenario, the terms of which were discussed earlier and are illustrated in table 1. The major differences in mandated volumes from 2015 levels are that the implied biodiesel mandate is increased by 84%, whereas the implied corn-ethanol mandate is increased by just 7%. Despite the modest increase in corn ethanol production, the ethanol blending ratio (fraction of ethanol in total gasoline fuel) exceeds 10%, a consequence of the decline in gasoline fuel demand associated with higher gasoline prices. As noted, ethanol blend ratios in excess of 10% would require some biofuel to be sold in higher-ethanol blends such as E85 suitable for FFVs. This raises an issue of feasibility of the mandate, and one of interpretation of our results. Because the 10.7% blend ratio of this scenario only marginally exceeds the blend wall, it seems quite feasible given current infrastructures.[19]

Both corn and soybean prices increase substantially, relative to the *status quo*. The increase in soybean price (10.6%) is larger than the increase in corn price (4.6%), relative to the *status quo*, a consequence of the need to expand biodiesel production to meet the advanced biofuel mandate. This is also reflected in a much higher biodiesel RIN price (again under the assumption of no biodiesel subsidy). The increased use of both biofuels, combined with an overall decline in gasoline fuel consumption, achieves some pollution reduction (unlike the 2015 mandates case). As for welfare measures, however, table 4 shows overall welfare is considerably lower with the 2022 mandates than with 2015 mandates. The increase in crop prices benefits farmers, as the agricultural sector's aggregate producer surplus is highest among the scenarios we have considered. Despite the further improvement in the US terms of trade (in addition to increased prices of agricultural exports we have a decrease in the price of crude oil imports, relative to 2015 mandates), overall welfare declines. This is because these pecuniary effects are offset by the efficiency cost of expanding biofuel production (the supply price of biodiesel is increased by $0.83 per gallon, and the supply price of ethanol also increases by $0.05 per gallon). In the end, our model shows that biodiesel produced from vegetable oil turns out to be a costly way to increase biofuel supply. The projected expansion of the cellulosic biofuel mandate also weighs heavily on the welfare impacts of the 2022 mandates scenario. The large excess cost of these biofuels relative to consumer value—captured by the D3 RIN price that we have assumed, based on current market conditions—makes expansion of cellulosic biofuel use particularly onerous.

Optimal mandates. One of the advantages of the structural model that we have developed is that we can compute "optimal" mandates. In this second best scenario, we take as given existing motor fuel taxes and ask what level of mandates would maximize the welfare function (Marshallian surplus net of external damages). The grid search method that we implemented identifies an optimal biodiesel mandate of 1.8 billion gallons, zero mandates for cellulosic biofuel, and an overall renewable fuel mandate of 18.6 billion gallons (implying an effective corn-based ethanol mandate of approximately 16.8 billion gallons). Thus, the constrained optimal mandates that we find would envision an 18% expansion of the implied corn-based ethanol mandate, relative to the year 2022 scenario, and a drastic reduction of the advanced biofuel mandate (including zero cellulosic biofuel). The corn price would increase, relative to both 2015 mandates and the year 2022 scenario, but the soybean price would decline.

The corn price increase results in higher marginal cost of supplying ethanol, and the ethanol price also increases. Consequently, the ethanol RIN price also increases. table 3 indicates that the biodiesel RIN price also increases with the optimal mandates, relative to 2015 mandates, despite the fact that soybean oil price is lower. Note, however, that the optimal mandate scenario presumes the elimination of the biodiesel subsidy ($1 per gallon), so that the RIN price in the optimal mandate case reflects the full extent of the marginal cost of biodiesel production in excess of its consumer valuation (if the $1 subsidy were preserved, the optimal mandates would entail essentially a zero RIN price for biodiesel).[20] These optimal mandates would result in higher emissions than with the projected 2022 mandates. The overall welfare gain associated with such optimal mandates, relative to 2015 mandates is $0.7 billion, but relative to the projected 2022 scenario the gain amounts to $5.2 billion.

The ethanol blending ratio with optimal mandates turns out to be 11.6%. Concerning feasibility, as discussed earlier (footnote 19), this blending may be supportable given current infrastructures. But, as highlighted by Anderson (2012), E10 and E85 are best viewed as imperfect substitutes on an energy-equivalent basis. Even if consumers only cared about the cost per mile of fuel, because E85 requires more frequent refilling than E10, and not all gas stations carry E85, there is a convenience cost to using E85. We have chosen not to embed this imperfect substitutability property in our demand specification.[21] As a result, we cannot offer a rigorous welfare assessment of optimal mandates when E85 consumption needs to be expanded beyond current patterns. Still, the welfare gain that we estimate from optimally rebalancing RFS mandates may be interpreted as the upper bound of the potential payoff of whatever investments may be required to accommodate the blend wall.[22]

Sensitivity Analysis

Inevitably, some of the assumed elasticity values or coefficients used to parameterize the model may be perceived as having a degree of arbitrariness. We note at this juncture that the existing econometric evidence can only be of partial help, both because of the limited number of relevant studies, and because the structure underlying existing econometric estimates may not be entirely consistent with the structure of this article's model. In any event, sensitivity analysis can be helpful to assess the robustness of the results to alternative parameter values. Here we present the results associated with alternative assumptions concerning the ROW elasticity of crude oil supply to the United States, and the ROW elasticities of demand for US agricultural exports. A more comprehensive set of sensitivity analyses is presented in the supplementary appendix online.

In the logic of the model, there are two distinct reasons for RFS policies: to correct the carbon pollution externality (under the presumption that biofuels are less polluting than fossil fuels); and, to exploit the terms of trade. Concerning the first of these objectives, the second best setting of the model needs to account for the fact that existing motor fuel taxes also ameliorate the carbon externality. Furthermore, as noted, insofar as these taxes are levied on a volume basis, they are inherently biased against biofuels (because the latter entail lower pollution effects and have lower energy content). This imbalance can, to a degree, be addressed by RFS mandates because these policy instruments work as a tax on fossil fuel and a subsidy for biofuel (in a revenue neutral fashion, as shown in Lapan and Moschini 2012). And because they tax products (fossil fuels) for which the United States is a net importer, and subsidize domestic use of products (corn and soybean products) for which the United States is a net exporter, RFS mandates can also improve the U.S. terms of trade.

To isolate the contribution of these various elements to the estimated market and welfare effects, table 5 reports counterfactual results for scenarios that postulate the absence of all or part of the terms of trade effects. Specifically, the columns labeled as "no TOT effects" presumes that the ROW excess supply of crude oil, and the ROW excess demand for agricultural products, are infinitely elastic (such that the prices of crude oil, corn, soybean oil and soybean meal are constant at the calibrated values). Under these assumptions, we evaluate both 2022 projected mandates and optimal mandates. Because by assumption there are no terms-of-trade effects here, we find that 2022 projected mandates would entail a large welfare loss (relative to the no RFS scenario) of $11.3 billion, despite the fact that they considerably decrease the carbon externality (because there is no leakage in this case). Without terms of trade effects we also find that there is no scope for biofuel policies. Note that, even without terms of trade effects, there remains market failure arguments for intervention (carbon externality and the overtaxing of biofuels by existing motor fuel taxes). But the assumed technological requirement for ethanol use as an oxygenate, which is binding at the optimal solution, make such considerations irrelevant.

The last four columns of table 5 decompose the importance of terms of trade as arising from the crude oil market or from agricultural markets. When there are no crude oil terms of trade, such that the price of crude oil is fixed at the baseline level, we find that 2022 mandate levels still entail considerable welfare loss relative to the no RFS scenario. Optimal mandates for this case are close to those reported in table 3 and lead to a $2.1 billion gain in overall welfare (relative to no RFS). If we do allow crude oil price to adjust, and simply postulate that the ROW demands for US agricultural exports are perfectly elastic, then the last two columns in table 5 indicate large welfare losses associated with 2022 mandates, and minor gains arising from optimal policies (a mere $0.15 billion more than in the no RFS scenario).

The combined evidence of tables 4 and 5 suggests that virtually all of the estimated increase in US aggregate welfare is ultimately due to the positive impacts that the RFS has on the US terms of trade. Mandates result in increased prices of corn and soybeans, and a decreased price of crude oil. Because the United States is a net exporter of corn and soybean products (both before and after the RFS), and a net importer of crude oil, these changed terms of trade are beneficial. Furthermore, it seems that the terms of trade effects arising from exports of agricultural commodities dominate the beneficial effects associated with decreased crude oil price (which are also affected by the leakage effect).

Comparison with Other Studies

Differing methodologies and empirical approaches makes comparison of our results with those of other studies perilous. Concerning market effects of the RFS, though, we note that our estimated agricultural price increases due to the RFS are quite similar to those obtained by Carter, Rausser and Smith (2016). Using a completely different methodology—a structural vector autoregression econometric approach—these authors estimate that the EISA additional 5.5 billion gallons ethanol requirement (relative to those envisioned in the 2005 legislation) caused a 31% long-run increase in corn prices. This is quite consistent with our higher estimate for the 2015 mandate levels (34% corn price increase), but our model traces the effects of a larger mandate level. Our estimated agricultural price increases are smaller than those obtained by Cui et al. (2011), reflecting the implications of a much more elaborate model as well as somewhat more conservative elasticity assumptions. Our model is unique in the existing literature, as noted earlier, as being able to articulate the impact of the RFS on soybean prices, not just corn prices.

Other studies have emphasized that the blend wall can make the RFS more costly. Similar to our study, Meiselman (2016) recognizes the RIN price linkages implied by the hierarchical structure of RFS mandates, but he only considers a closed economy scenario and does not envision supply-side interactions between biodiesel and ethanol production. He finds that increasing the mandate around the blend wall would reduce GHG emission, but this would entail a very high (marginal) social cost (\$800/tCO_2e). Although we do not have a comparable scenario for this estimate, we note that our projected 2022 mandate levels improve on carbon emission, both relative to 2015 levels and to the no RFS scenario, although welfare declines. The latter conclusion, of course, depends on our assumed social cost of carbon (γ =\$20/tCO_2e). To investigate how the welfare result is affected by the assumed social cost of carbon, we computed two break-even levels for the γ parameter. We find that a social cost of carbon of \$110/tCO_2 would make welfare with the 2022 mandates the same as in the "No RFS" scenario, but that it would take a social cost of carbon of \$192/tCO_2 to make welfare with the 2022 mandates the same as with 2015 mandates.

Conclusion

This article analyzes some of the market and welfare impacts of US biofuel support policies under the RFS program. To do so, we have constructed a tractable multi-market model that incorporates biodiesel markets as well as ethanol markets, thereby extending previous work that focused solely on gasoline-ethanol blends. We show how compliance requirements on obligated parties, which are mediated by RIN prices, can be used to identify the relevant zero-profit conditions required to close the model. Within this framework, the model is calibrated to match market data for the 2015 benchmark year. The model can then be solved and simulated to study counterfactual policy scenarios, yielding equilibrium prices, quantities and welfare impacts. A first-order impact of the RFS is to divert large amounts of corn and soybean oil to biofuel production. This reduces the amount of these products available for export, and the RFS-induced biofuels production also marginally lowers the US demand for refined fossil fuels. Given that the United States are a net importer of crude oil and net exporter of corn and soybean products, the favorable terms-of-trade effects that arise because of the RFS are quite important in order to assess the resulting welfare impacts. Having endogenized the relevant agricultural and energy markets, the model that we construct offers an ideal tool to assess the overall consequences, from the point of view of the United States, of current RFS policies and alternative paths that may be considered going forward.

The results that we have presented confirm that the current RFS program considerably benefits the agriculture sector. Compared with the *status quo ante* situation (no RFS), we find that current biofuel policies increase corn and soybean prices by 34% and 9% , respectively, and also lead to a 1.4% decline in crude oil price. The welfare gain to the United States that can be imputed to the RFS, in 2015, is estimated at about $2.6 billion. Virtually all of these US welfare gains are due to the impact of RFS policies on the terms of trade. Furthermore, the most relevant effects are those associated with the RFS impacts on the price of key US agricultural exports (corn and soybean products). The RFS net impact on carbon emission is nil in the benchmark year, and minimal with the projected 2022 mandate levels. One of the main reasons for this finding is the leakage effects that arise because of increased consumption of fossil fuels in the ROW due to the RFS-induced decline in crude oil price.

There is considerable uncertainty, and policy debate, concerning future implementation of the RFS. The model that we have developed can be used to assess the market and welfare consequences of alternative paths. We find that full implementation of the EISA statutory 2022 mandate levels (except for the widely expected extensive waiver of cellulosic biofuel mandates) would be costly to the United States. This is because biodiesel, as the marginal fuel of choice to meet the advanced biofuel mandate, does not appear to be an efficient enough tool. Alternatively, if we ask what the optimal mandates levels would be in the context of the model, we find that it would be desirable to expand corn-based ethanol production beyond the 15 billion gallon cap envisioned by the EISA legislation (concomitantly, optimal mandates suggest that a reduction of biodiesel production from current levels is also desirable, and no cellulosic biofuel production). As noted, of course, the viability of such an option may need to deal with the blend wall issue. In any event, relative to 2015 mandate levels, these optimal (second best) mandates produce limited welfare gains. This is because, as documented in the analysis we have presented, it is the impact of the RFS on agricultural terms of trade that is most important. For these effects to remain sizeable, the magnitude of US exports cannot be curtailed too much.

In addition to quantifying the overall welfare gains, the model permits a characterization of the re-distribution effects implied by various scenarios. The magnitudes of such effects are quite large, and the documented impacts—agriculture is the big winner—may help to rationalize some of the political economy features of the debate about the future of the RFS. Although our analysis has been consistently articulated in terms of US welfare, our finding that the predominant welfare impacts are rooted in terms of trade effects suggests that this domestic program has clear "beggarthy-neighbor" implications. Obligations undertaken within the World Trade Organization (WTO) restrain the ability of the United States to use border policies to shift to other countries some of the costs of its long-standing agricultural support objectives. RFS provisions, while *prima facie* consistent with the national treatment principle of the WTO, are apparently effective at shifting some of their costs onto foreign constituencies. The fact that the latter represent mostly consumers of agricultural products adds weight to the food-versus-fuel debate. Finally, our finding that the RFS has minimal impacts on reducing global carbon emissions suggests that, from an international perspective, the scope of biofuel policies to improve global welfare may be extremely limited.

Table 1. Statutory Mandates, EPA Final Rulings, and 2022 Scenario (billion gallons)

	2015		2016		2017		2022	
	EISA	EPA	EISA	EPA	EISA	EPA	EISA	Projected
Renewable fuel	**20.5**	**16.93**	**22.25**	**18.11**	**24.0**	**19.28**	**36.0**	**20.787**
Advanced biofuel	5.5	2.88	7.25	3.61	9.0	4.28	21.0	5.787
Biodiesel	≥ 1.0	1.73	≥ 1.0	1.90	≥ 1.0	2.00	≥ 1.0	… [a]
Cellulosic biofuel	3.0	0.123	4.25	0.230	5.5	0.311	16.0	0.787 [b]
Non-cellulosic advanced biofuel	*2.5*	*2.757*	*3*	*3.38*	*3.5*	*3.969*	*5*	*5*
Corn ethanol	*15*	*14.05*	*15*	*14.5*	*15*	*15*	*15*	*15*

Source: Schnepf and Yacobucci (2013) and EPA (2016). All quantities are in ethanol-equivalent gallons except for biodiesel, which are in physical volume.

Note: [a] Biodiesel produced as needed (assumed to be the marginal advanced fuel); [b] Linear trend projection based on 2014-2017 EPA rulings ($R^2 = 0.998$).

Table 2. Elasticities

Parameter	Symbol	Value	Source/explanation
Corn acreage own-price supply elasticity	η_{cc}^{L}	0.36	Estimated. [d]
Corn acreage cross-price supply elasticity	η_{cs}^{L}	−0.18	Estimated. [d]
Soybean acreage own-price supply elasticity	η_{ss}^{L}	0.23	Estimated. [d]
Corn yield own-price elasticity	η_{cc}^{y}	0.05	Berry and Schlenker (2011)
Soybean yield own-price elasticity	η_{ss}^{y}	0.01	Berry and Schlenker (2011)
Domestic demand elasticity of corn	ε_{cc}	−0.20	de Gorter and Just (2009)
Domestic demand elasticity of soybean meal	ε_{mm}	−0.20	Bekkerman et al. (2012) [a]
Domestic demand elasticity of soybean oil	ε_{vv}	−0.20	Bekkerman et al. (2012) [a]
Cross-elasticity of domestic corn demand w.r.t. p_m	ε_{cm}	0.065	Calculated [b, d] ($\varepsilon_{mc} = 0.105$)
Cross-elasticity of domestic corn demand w.r.t. p_v	ε_{cv}	0.014	Calculated [b, d] ($\varepsilon_{vc} = 0.105$)
Cross-elasticity of domestic meal demand w.r.t. p_v	ε_{mv}	0.014	Calculated [b, d] ($\varepsilon_{vm} = 0.065$)
ROW import demand elasticity of corn	$\bar{\varepsilon}_{cc}$	−2.50	Calculated [d]
ROW import demand elasticity of soybean meal	$\bar{\varepsilon}_{mm}$	−1.60	Calculated [d]
ROW import demand elasticity of soybean oil	$\bar{\varepsilon}_{vv}$	−1.30	Calculated [d]
Domestic supply elasticity of crude oil	η_R	0.25	EIA (2014)
ROW export supply elasticity of crude oil	$\bar{\chi}_R$	4.40	Assumed [d]
Domestic demand elasticity of gasoline fuel	ε_{gg}	−0.35	Bento et al. (2009)
Domestic demand elasticity of diesel fuel	ε_{dd}	−0.15	Assumed [c, d]
Domestic demand elasticity of other refined petroleum products	ε_{hh}	−0.50	Assumed [c, d]

Note: [a] Rounded values. [b] Calculated assuming that all of the Allen-Uzawa elasticities of substitution are the same. [c] Based on Dahl (2012) and Winebrake et al. (2015). [d] See the supplementary appendix online for more details.

Table 3. Market Effects of Alternative Policy Scenarios

	Laissez Faire	No RFS	2015 Mandates	2022 Mandates	Optimal Mandates
Gasoline motor fuel tax ($/gal.)		0.449	0.449	0.449	0.449
Diesel motor fuel tax ($/gal.)		0.516	0.516	0.516	0.516
Biodiesel subsidy ($/gal.)			1.000		
Cellulosic biofuel mandate (billion units)			0.123	0.787	
Advanced biofuel mandate (billion units)			2.880	5.787	1.795
Renewable biofuel mandate (billion units)			16.930	20.787	18.616
Corn price ($/bu.)	3.08	2.75	3.68	3.85	3.88
Soybean price ($/bu.)	9.26	9.23	10.10	11.18	9.66
Soybean meal price ($/ton)	378.42	382.07	368.49	362.09	368.20
Soybean oil price (¢/lb.)	22.20	21.17	31.60	42.44	27.81
Crude oil price ($/bbl)	49.83	49.10	48.40	48.00	48.36
Gasoline fuel price ($/GEEG)	2.03	2.35	2.22	2.30	2.15
Diesel fuel price($/DEEG)	1.39	1.98	2.23	2.12	2.46
Gasoline price ($/gal.)	2.03	1.90	1.72	1.74	1.63
Diesel price ($/gal.)	1.39	1.47	1.67	1.50	1.87
Ethanol price ($/gal.)	1.43	1.33	1.61	1.66	1.66
Biodiesel (supply) price ($/gal.)	2.93	2.85	3.65	4.48	3.36
Other refined products' price ($/KEEG)	1.08	1.17	1.26	1.31	1.27
RIN price for ethanol ($/unit)			0.49	0.49	0.60
RIN price for biodiesel ($/unit)			0.73	2.02	1.06
Ethanol quantity (billion gal.) [a]	7.946	4.123	14.140	15.167	16.909
Blending ratio of ethanol (%) [b]	5.457	3.000	9.877	10.692	11.600
Biodiesel quantity (billion gal.) [a]	0.686	0.686	1.779	3.275	1.138
Gasoline fuel quantity (billion GEEGs)	143.265	136.216	139.051	137.349	140.750
Diesel fuel quantity (billion DEEGs)	49.202	47.334	46.548	46.898	45.846
Other refined products (billion KEEGs)	82.097	79.236	76.476	74.887	76.314
Corn production (billion bus.)	13.474	12.959	14.216	14.218	14.643
Soybean production (billion bus.)	4.002	4.082	3.927	3.984	3.835
Corn demand (billion bus.)	8.089	8.231	7.851	7.805	7.752
Corn export (billion bus.)	2.583	2.993	1.833	1.615	1.585
Soybean meal demand (million tons)	47.113	46.540	48.408	49.052	48.609
Soybean meal export (million tons)	54.133	53.236	56.572	58.146	56.643
Soybean oil demand (billion lbs.)	12.801	12.773	12.260	11.467	12.623
Soybean oil for biodiesel (billion lbs.)			8.363	19.803	3.457
Soybean oil export (billion lbs.)	31.096	32.046	22.421	12.425	25.918
Crude oil domestic supply (billion bbl)	3.475	3.462	3.450	3.443	3.449
Crude oil import (billion bbl)	3.284	3.092	2.907	2.800	2.896
Crude oil foreign demand (billion bbl)	23.131	23.201	23.268	23.307	23.272

Note: [a] Quantities (from all sources) blended into US fuel supply. [b] Calculated by using physical units (ratio of gallons of ethanol to gallons of gasoline fuel).

Table 4. Welfare Effects of Alternative Policies (changes relative "No RFS" scenario)

	Laissez Faire	2015 Mandates	2022 Mandates	Optimal Mandates
Social welfare ($ billion)	**2.562**	**2.647**	**-1.900**	**3.344**
Pollution effect [a]	-1.866	-0.106	0.422	-0.336
Tax revenue	-86.165	0.516	2.168	2.987
P.S. Agriculture [b]	9.266	14.112	21.783	13.481
P.S. Crude oil supply [b]	2.519	-2.422	-3.814	-2.564
Efficiency cost of cellulosic biofuel [c]		-0.221	-1.417	
C.S. Crop products' demand [d]	-2.652	-8.154	-10.496	-9.223
C.S. Fuel demand [d]	73.851	6.008	0.507	6.495
Gasoline fuel demand	45.000	17.828	7.080	28.688
Diesel fuel demand	28.851	-11.820	-6.573	-22.194
C.S. Other refined products [d]	7.608	-7.086	-11.054	-7.495
GHG emissions (million tCO_2e) [a]	**93.28**	**5.28**	**-21.09**	**16.80**
Changes in the United States	128.52	-28.73	-74.68	-19.21
Changes in the ROW	-35.24	34.01	53.60	36.01

Note: [a] In the "No RFS" scenario the GHG emission level is 14,684 [2,976 (US) + 11,709 (ROW)] million tCO_2e, the monetary cost of which is $293.7 billion. [b] P.S. = producer surplus. [c] Computed based on a D3 RIN price of $1.80. [d] C.S. = consumer surplus.

Table 5. Sensitivity Analysis: Terms-of-Trade (TOT) Effects

	Baseline	No TOT effects		No crude oil TOT		No agricultural TOT	
Policies / Market Effects	2015 Mandates	2022 Mandates	Optimal Mandates	2022 Mandates	Optimal Mandates	2022 Mandates	Optimal Mandates
Gasoline motor fuel tax ($/gal.)	0.449	0.449	0.449	0.449	0.449	0.449	0.449
Diesel motor fuel tax ($/gal.)	0.516	0.516	0.516	0.516	0.516	0.516	0.516
Biodiesel subsidy ($/gal.)	1.000						
Cellulosic biofuel mandate (billion units)	0.123	0.787		0.787		0.787	
Advanced biofuel mandate (billion units)	2.880	5.787	1.117	5.787	1.454	5.787	1.117
Renewable biofuel mandate (billion units)	16.930	20.787	5.159	20.787	16.723	20.787	9.662
Corn price ($/bu.)	**3.68**	**3.68**	**3.68**	3.85	3.73	**3.68**	**3.68**
Soybean price ($/bu.)	**10.10**	**10.10**	**10.10**	11.18	9.48	**10.10**	**10.10**
Soybean meal price ($/ton)	**368.49**	**368.49**	**368.49**	362.09	370.52	**368.49**	**368.49**
Soybean oil price (¢/lb.)	**31.60**	**31.60**	**31.60**	42.44	25.78	**31.60**	**31.60**
Crude oil price ($/bbl)	**48.40**	**48.40**	**48.40**	**48.40**	**48.40**	48.03	48.88
Gasoline price ($/gal.)	1.72	1.76	1.88	1.75	1.65	1.75	1.79
Diesel price ($/gal.)	1.67	1.50	1.44	1.52	1.84	1.48	1.65
Ethanol price ($/gal.)	1.61	1.61	1.61	1.66	1.62	1.61	1.61
Biodiesel (supply) price ($/gal.)	3.65	3.65	3.65	4.48	3.20	3.65	3.65
RIN price for ethanol ($/unit)	0.49	0.44	0.41	0.49	0.55	0.44	0.46
RIN price for biodiesel ($/unit)	0.73	1.47		2.00	0.98	1.48	
Ethanol quantity (billion gal.)	14.140	15.167	4.129	15.167	15.357	15.167	8.633
Blending ratio of ethanol (%)	9.877	10.685	3.000	10.703	10.589	10.675	6.140
Biodiesel quantity (billion gal.)	1.779	3.275	0.686	3.275	0.911	3.275	0.686
Corn export (billion bu.)	1.833	1.568	4.628	1.615	1.769	1.568	3.370
Soybean meal export (million tons)	56.572	57.421	47.636	58.146	56.074	57.421	51.657
Soybean oil export (billion lbs.)	22.421	10.982	30.785	12.425	27.788	10.982	30.785
Crude oil domestic supply (billion bbl)	3.450	3.450	3.450	3.450	3.450	3.443	3.458
Crude oil import (billion bbl)	2.907	2.797	3.114	2.786	2.933	2.810	3.033
Welfare Impacts (relative to "No RFS")							
Social welfare ($ billion)		-11.268	0.0	-3.725	2.143	-9.522	0.146
Pollution effect		1.549	0.0	1.696	0.361	0.330	-0.191
Tax revenue		2.088	0.0	1.880	2.527	2.364	1.163
P.S. Agriculture		-1.243	0.0	21.307	10.686	-0.797	-1.412
P.S. Crude oil supply		0.0	0.0	0.0	0.0	-3.646	-0.741
Efficiency cost of cellulosic biofuel		-1.417	0.0	-1.417	0.0	-1.417	0.0
C.S. Crop products' demand		0.0	0.0	-10.490	-7.921	0.0	0.0
C.S. Fuel demand		-0.985	0.0	-4.933	3.120	4.219	3.518
C.S. Other refined products		-11.260	0.0	-11.768	-6.629	-10.576	-2.192
GHG emissions (million tCO_2e)		-77.45	0.0	-84.81	-18.04	-16.52	9.55
Changes in the United States		-77.45	0.0	-84.81	-18.04	-67.76	-0.85
Changes in the ROW		0.0	0.0	0.0	0.0	51.24	10.40

References

Anderson, S.T. 2012. "The Demand for Ethanol as a Gasoline Substitute." *Journal of Environmental Economics and Management* 63(2): 151-168.

Beckman, J., A. Borchers and C.A. Jones. 2013. *Agriculture's Supply and Demand for Energy and Energy Products*. Washington, DC: U.S. Department of Agriculture, Economic Information Bulletin No. 112, May.

Bento, A.M., L.H. Goulder, M.R. Jacobsen, and R.H. Von Haefen. 2009. "Distributional and Efficiency Impacts of Increased US Gasoline Taxes." *American Economic Review* 99(3): 667-699.

Berry, S. 2011. "Biofuels Policy and the Empirical Inputs to GTAP Models." Working paper, Department of Economics, Yale University, January.

Berry, S., and W. Schlenker. 2011. "Technical Report for the ICCT: Empirical Evidence on Crop Yield Elasticities." International Council on Clean Transportation, August.

Bekkerman, A., N.E. Piggott, B.K. Goodwin, and K. Jefferson-Moore. 2012. "A Market-based Mitigation Program for Wind-borne Diseases." *Agricultural and Resource Economics Review*, 41(2): 175-188.

Brorsen, W. 2015. "Projections of U.S. Production of Biodiesel Feedstock." Report prepared for Union of Concerned Scientists and The International Council on Clean Transportation, July.

Carter, C.A., G.C. Rausser and A. Smith. 2016. Forthcoming. "Commodity Storage and the Market Effects of Biofuel Policies." *American Journal of Agricultural Economics*, in press.

Coglianese, J., L.W. Davis, L. Kilian, and J.H. Stock. 2017. "Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand." *Journal of Applied Econometrics* 32: 1-15.

Cui, J., H. Lapan, G. Moschini, and J. Cooper. 2011. "Welfare Impacts of Alternative Biofuel and Energy Policies." *American Journal of Agricultural Economics*, 93(5): 1235-1256.

Dahl, C.A. 2012. "Measuring Global Gasoline and Diesel Price and Income Elasticities." *Energy Policy* 41:2-13.

Difiglio, C. 2014. "Oil, Economic Growth and Strategic Petroleum Stocks." *Energy Strategy Reviews* 5: 48-58.

de Gorter, H., and D.R. Just. 2009. "The Economics of a Blend Mandate for Biofuels." *American Journal of Agricultural Economics* 91(3): 738–750.

———. 2010. "The Social Costs and Benefits of Biofuels: The Intersection of Environmental, Energy and Agricultural Policy." *Applied Economic Perspectives and Policy* 32(1): 4-32.

de Gorter, H., D. Drabik, and D.R. Just. 2015. *The Economics of Biofuel Policies: Impacts on Price Volatility in Grain and Oilseed Market*. NY: Palgrave-Macmillan.

EIA (US Energy Information Administration). 2014. *International Energy Module of the National Energy Modeling System: Model Documentation*, July.

———. 2016. *Annual Energy Outlook 2016*, August.

EPA (US Environmental Protection Agency). 2010. *Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis*. EPA-420-R-10-006, February.

———. 2016. "Renewable Fuel Standard Program: Standards for 2017 and Biomass-Based Diesel Volume for 2018." *Federal Register*, Vol. 81, No. 238, pp. 89746-89804. Monday, December.

Felder, S. and T.F. Rutherford. 1993. "Unilateral Reductions and Carbon Leakage: The Effect of International Trade in Oil and Basic Materials." *Journal of Environmental Economics and Management* 25(2): 162–176.

Greene, D.L., and C. Liu. 2015. "US Oil Dependence 2014: Is Energy Independence in Sight?" *Energy Policy* 85: 126-137.

Hendricks, N.P., A. Smith, and D.A. Sumner. 2014. "Crop Supply Dynamics and the Illusion of Partial Adjustment." *American Journal of Agricultural Economics*, 96(5): 1469-1491.

Hoel, M. 1991. "Global Environmental Problems: The Effects of Unilateral Actions Taken by One Country." *Journal of Environmental Economics and Management*. 20(1): 55-70.

Hoffman, L.A., and A. Baker. 2011. *Estimating the Substitution of Distillers' Grains for Corn and Soybean Meal in the US Feed Complex*. US Department of Agriculture, Economic Research Service, Report FDS-11-I-01, October.

Holland, S.P., J.E. Hughes, C.R. Knittel, and N.C. Parker. 2015. "Some Inconvenient Truths about Climate Change Policy: The Distributional Impacts of Transportation Policies." *Review of Economics and Statistics*, 97(5): 1052-1069.

Hughes, J.E., C.R. Knittel, and D. Sperling. 2008. "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand." *Energy Journal* 29(1): 93-114.

Irwin, S. 2015. "Why Do Blenders Share Retroactively Reinstated Tax Credits with Biodiesel Producers?" *farmdoc daily* (5): 133, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. July.

Irwin, S., and D. Good. 2016. "RFS Standards Beyond 2017—Biodiesel or Bust?" *farmdoc daily* (6): 104, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. June.

Knittel, C.R., Meiselman, B.S. and Stock, J.H. 2015. "The Pass-Through of RIN Prices to Wholesale and Retail Fuels under the Renewable Fuel Standard." *NBER Working Paper* No. w21343, National Bureau of Economic Research, July.

Lade, G.E., C-Y. C. Lin Lawell, and A. Smith. 2016. "Policy Shocks and Market-Based Regulations: Evidence from the Renewable Fuel Standard." *Working Paper*, University of California-Davis. March.

Lapan, H. and G. Moschini. 2012. "Second-Best Biofuel Policies and the Welfare Effects of Quantity Mandates and Subsidies." *Journal of Environmental Economics and Management* 63(2): 224-241.

Lence, S.H. 2014. "Farmland Prices: Is This Time Different?" *Applied Economic Perspectives and Policy* 36(4): 577-603.

Liao, K., S. Pouliot, and B. Babcock. 2016. *Estimating Willingness to Pay for E85 in the United States*. Working Paper 16-wp562, Center for Agricultural and Rural Development, Iowa State University, November.

Lin, C.Y.C. and L. Prince. 2013. "Gasoline Price Volatility and the Elasticity of Demand for Gasoline." *Energy Economics* 38: 111-117.

McPhail, L., P. Westcott and H. Lutman. 2011. *The Renewable Identification Number System and US Biofuel Mandates*. US Department of Agriculture, Economic Research Service, Report BIO-03, November.

Meiselman. B.S. 2016. "Breaching the Blendwall: RINs and the Market for Renewable Fuel." Working Paper, Department of Economics, University of Michigan, February.

Moschini, G., J. Cui and H. Lapan. 2012. "Economics of Biofuels: An Overview of Policies, Impacts and Prospects." *Bio-based and Applied Economics* 1(3): 269-296.

Mumm, R.H., P.D. Goldsmith, K.D. Rausch, and H.H. Stein. 2014. "Land Usage Attributed to Corn Ethanol Production in the United States: Sensitivity to Technological Advances in Corn Grain Yield, Ethanol Conversion, and Co-product Utilization." *Biotechnology for biofuels* 7, article 61.

Parry, I.W.H. and K.A. Small. 2005. "Does Britain or the United States Have the Right Gasoline Tax?" *American Economic Review* 95(4): 276–89.

Rosegrant, M.W. and S. Msangi. 2014. "Consensus and Contention in the Food-Versus-Fuel Debate." *Annual Review of Environment and Resources* 39:271-294.

Piggott, N.E. and M.K. Wohlgenant. 2002. "Price Elasticities, Joint Products, and International Trade." *Australian Journal of Agricultural and Resource Economics* 46(4): 487-500.

Pouliot, S. and B.A. Babcock. 2016. "Compliance Path and Impact of Ethanol Mandates on Retail Fuel Market in the Short Run." *American Journal of Agricultural Economics*. 98(3): 744-764.

Salvo, A. and C. Huse, 2013. "Build It, but Will They Come? Evidence from Consumer Choice between Gasoline and Sugarcane Ethanol." *Journal of Environmental Economics and Management* 66(2): 251-279.

Schnepf, R. and B.D. Yacobucci. 2013. *Renewable Fuel Standard (RFS): Overview and Issues*. Congressional Research Services Report No. R40155, October.

Schroeder, A. 2015. *A Primer on Motor Fuel Excise Taxes and the Role of Alternative Fuels and Energy Efficient Vehicles*. Technical Report NREL/TP-5400-60975. National Renewable Energy Laboratory (NREL), Golden, CO, August.

Searchinger, T., R. Heimlich, R.A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.H. Yu. 2008. "Use of US Croplands for Biofuels Increases Greenhouse Gases through Emissions from Land-Use Change." *Science* 319(5867): 1238-1240.

Sobolevsky, A., G. Moschini and H. Lapan. 2005. "Genetically Modified Crops and Product Differentiation: Trade and Welfare Effects in the Soybean Complex." *American Journal of Agricultural Economics* 87(3): 621-644.

Stern, N.H. 2007. *The Economics of Climate Change: The Stern Review.* Cambridge, UK: Cambridge University Press.

Stock, J.H. 2015. *The Renewable Fuel Standard: A Path Forward.* Center for Global Energy Policy, SIPA, Columbia University.

Thurman, W.N. 1991. "Applied General Equilibrium Welfare Analysis." *American Journal of Agricultural Economics* 73(5): 1508-16.

Tol, R.S.J. 2009. "The Economic Effects of Climate Change." *Journal of Economic Perspectives* 23(2): 29-51.

Winebrake, J.J., E.H. Green, B. Comer, C. Li, S. Froman, and M. Shelby. 2015. "Fuel Price Elasticities in the US Combination Trucking Sector." *Transportation Research Part D: Transport and Environment* 38: 166-177.

Wright, B.D. 2014. "Global Biofuels: Key to the Puzzle of Grain Market Behavior." *Journal of Economic Perspectives* 28(1): 73-97.

US Government. 2016. *Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866*. Interagency Working Group on Social Cost of Greenhouse Gases, August.

Appendix

Table A1. Technical Coefficients

Parameter	Symbol	Value	Source/explanation
Ethanol production coefficient (gal./bu.)	α_e	2.8	Cui et al. (2011)
Ethanol by-product replacing corn in feed, as fraction of corn used for ethanol	δ_1	0.218	$\delta_1 = 0.307 \times 0.71$
Ethanol by-product replacing soy meal in feed, as fraction of corn used for ethanol	δ_2	0.003	$\delta_2 = (0.307 \times 0.29)(56/2000)$
Biodiesel production coefficient (gal./lb.)	α_b	0.131	EIA [a]
Soybean meal production coefficient (tons/bu.)	α_m	0.024	$\alpha_m = 45.1/1{,}873$ [b]
Soybean oil production coefficient (lbs./bu.)	α_v	11.425	$\alpha_v = 21{,}399/1{,}873$ [b]
Gasoline heat content (mil. BTUs/bbl)	ζ_1	5.06	EIA
Diesel heat content (mil. BTUs/bbl)	ζ_2	5.77	EIA
Ethanol heat content (mil. BTUs/bbl)	ζ_3	3.558	EIA
Biodiesel heat content (mil. BTUs/bbl)	ζ_4	5.359	EIA
Ethanol energy equivalent coefficient (GEEGs/gal.)	ζ_e	0.703	$\zeta_e = \zeta_3 / \zeta_1$
Biodiesel energy equivalent coefficient (DEEGs/gal.)	ζ_b	0.929	$\zeta_b = \zeta_4 / \zeta_2$
Gasoline production coefficient (gal./bbl)	β_g	21.286	$\beta_g = x_g / x_R$
Diesel production coefficient (gal./bbl)	β_d	9.115	$\beta_d = x_d / x_R$
Other refined petroleum products production coefficient (KEEGs/bbl)	β_h	13.96	$\beta_h = (42 \times 1.063 - \beta_g - \beta_d) \times 0.98$ [c]
"Equivalence value" of RIN generation for biodiesel	ϑ	1.5	Schnepf & Yacobucci (2013)
Fraction of cellulosic ethanol in cellulosic biofuel	μ_{ce}	0.02, 0.10	Assumed [d]
Required fraction of ethanol as oxygenate	μ_{oxy}	0.03	Assumed

Note: [a] Corresponds to 7.65 pounds of soybean oil per gallon of biodiesel.

[b] Data taken from https://www.ers.usda.gov/data-products/oil-crops-yearbook/

[c] The coefficient 1.063 accounts for 6.3% average "refinery yield" gains accrued in 2015, whereas 0.98 is the weighted average of kerosene energy equivalence for petroleum products in this category.

[d] The benchmark value of $\mu_{ce} = 0.02$ is estimated from EPA's "RIN generation summary" over 2014-2016. For the 2022 (and optimal mandates) scenarios we set $\mu_{ce} = 0.10$, consistent with data and discussion contained in EPA (2016).

Table A2. GHG Emission Rates (kg CO_2e/gallon) and Social Marginal Damage

Parameter	Symbol	Value	Source/explanation
Gasoline	E_g	11.831	EPA (2010)
Diesel	E_d	13.327	EPA (2010)
Corn-based ethanol	E_e	6.572	$E_g \times 0.79 \times \zeta_e$ (EPA 2010) [a]
Sugarcane ethanol	E_{se}	3.245	$E_g \times 0.39 \times \zeta_e$ (EPA 2010) [a]
Cellulosic biofuel	E_{ce}	3.328	$E_g \times 0.40 \times \zeta_e$ [a]
Biodiesel	E_b	5.332	$E_d \times 0.43 \times \zeta_b$ (EPA 2010) [a]
Other refined petroleum products	E_h	9.410	EIA [b]
Crude oil (kg CO_2e/bbl)		504.67	Computed from E_g, E_d and E_h
Marginal emissions damage ($/t$CO_2$)	γ	20.0	Stern (2007) and Cui et al. (2011)

Note: [a] Life-cycle GHG emissions rates per energy unit relative to gasoline and diesel baselines (EPA 2010, Chapter 2.6). [b] Weighted average of CO_2 emissions rates from various other refined products (see text).

Footnotes

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[1] To keep the analysis tractable we avoid the structural representation of other vegetable oil industries. Insofar as soybean oil is a close substitute for other vegetable oils that can also serve as feedstock for biodiesel production, this simplification would seem to entail little loss of generality.

[2] RINs are identifiers assigned to biofuel batches at production. They are "separated" from the physical product when the biofuel is blended with fossil transportation fuel. Such separated RINs can then be used by obligated parties to show compliance. Obligated parties can meet the RIN requirements by buying a sufficient amount of biofuel themselves or, alternatively, by buying separated RINs from other parties (McPhail, Westcott and Lutman, 2011).

[3] Although the biodiesel mandate is defined in physical volume, when biodiesel is used to meet the advanced biofuel standard, or the overall renewable fuel standard, each gallon is multiplied by an "equivalence value" (either 1.5 or 1.7) (Schnepf and Yacobucci 2013).

[4] Lade, Lin Lawell and Smith (2016) also find that biodiesel served as the marginal biofuel for RFS compliance in 2013. Irwin and Good (2016) derive mandate projections to 2022 very similar to ours.

[5] The supplementary appendix online provides an explicit justification for this assumption based on Beckman, Borchers and Jones (2013). Note that, whereas this simplifies the representation of the relevant equilibrium conditions, we still can account for the impact of changing equilibrium energy prices (across scenarios) in the computation of agricultural producer surplus.

[6] Sobolevsky, Moschini and Lapan (2005) explain why, given the maintained assumptions, the location of soybean processing is undetermined such that the only meaningful trade flows that can be recovered by competitive equilibrium pertain to the factor content of trade.

[7] In the RFS regulation, these fuels are denoted as D6, D5, D4 and D3, respectively.

[8] Most of the current production of cellulosic biofuel takes the form of compressed natural gas and liquefied natural gas derived from biogas (EPA 2016). Note, however, that the full mandate x_{ce}^{M} is relevant for the purpose of refiners/blenders' cost of compliance with the RFS, as discussed below.

[9] The marketing year runs September to August for corn and soybeans, and October to September for soybean meal and soybean oil.

[10] The relative lifecycle GHG emissions rates for corn-ethanol, sugarcane ethanol, and biodiesel—when fuels are measured in energy equivalent units—are 79%, 39% and 43%, respectively, compared to corresponding fossil fuel baselines. For cellulosic biofuel, the EPA requires that

qualifying products provide at least a 60% emission savings relative to fossil fuels, so we conservatively assumed this limit value in calculating the carbon emission coefficient in table A2.

[11] These products—aviation gasoline, kerosene-type jet fuel, propane, kerosene and residual fuel oil—account for 52%, by weight, of all other refined petroleum products. Owing to the assumed Leontief technology, the assumed emission rates for refined products can alternatively be expressed per units of crude oil consumption, and this rate is used to compute GHG changes in the ROW.

[12] The US government's estimate for the 2015 social cost of carbon (in 2007 dollars) ranges from \$11/ton of CO_2 (when using a 5% discount rate) to \$56/ton of CO_2 (when using a 2.5% discount rate), with an additional estimate of \$105/ton of CO_2 to represent higher-than-expected impacts of temperature changes (US Government 2016, p. 4).

[13] The average annual biodiesel price for 2015 that we computed from USDA data \$2.83/gallon. (National Weekly Ag Energy Round-Up, USDA Ag Marketing Service).

[14] Computation of this price requires simultaneously solving equations (26), (32) and (33), which also yields the blended fuel prices p_{gf} and p_{df} at the calibration point.

[15] The core value for cellulosic biofuel RINs, used to impute the social cost of (exogenous) cellulosic biofuel mandates, is estimated at \$1.80 per unit (from the average of D6 RIN prices, over the relevant period, as reported in "PFL Weekly RIN Recap").

[16] For this scenario, however, we assume that even without biofuel policies a certain amount of ethanol is used by blenders as a gasoline oxygenate. This is modeled as a technological minimum requirement, which is set at 3% of the blended gasoline fuel. The supplementary appendix online provides the equilibrium conditions for the case when this requirement is binding.

[17] The elasticity of the ROW crude oil demand used to estimate the leakage effect is $\bar{\varepsilon}_R = -0.2$. As detailed in the supplementary appendix online, this is the demand elasticity that is implied by the model's assumed elasticities for refined petroleum products' demands. This value was also used to rationalize the ROW crude oil export supply elasticity used in the model.

[18] Given the assumed emission rates and social cost of carbon, the per-gallon Pigouvian taxes needed to correct the externality would be \$0.237 for gasoline, \$0.267 for diesel, \$0.131 for corn-based ethanol, and \$0.106 for biodiesel. Of course, motor fuel taxes can be rationalized in the pursuit of more than just reduction in carbon emissions, such as reducing congestion and other externalities associated with vehicle use (Parry and Small 2005).

[19] In a recent intercept survey carried out in five US states, Liao, Pouliot and Babcock (2016) find that about 50% of FFV motorists use E85. At present, FFVs constitute approximately 8.3% of the US fleet of gasoline-powered cars and light trucks (EIA 2016). Because E85 on average contains 74% ethanol, if half of FFV miles were to be fueled by this blend, the ethanol “saturation point” would be about 12.2%. Liao, Pouliot and Babcock (2016) also find that E85 is sold at a premium relative to E10 (on an energy equivalent basis), so that a higher saturation point could actually be supported if E85 were to be priced more aggressively.

[20] Similar considerations also pertain to the reported RIN prices for the year 2022 scenario.

[21] As consumers are likely heterogeneous with respect to the convenience cost of refueling, an accurate aggregate demand representation of this imperfect substitutability would require considerable information on the distribution of the relevant consumer heterogeneity, making calibration nontrivial. The alternative of representing imperfect substitutability between E10 and E85 by means of CES demand functions, as done by Meiselman (2016), does not appear attractive in this context.

[22] A more accurate assessment would consider mandate levels that are optimal given the blend wall, with an explicit representation of the imperfect substitutability between E10 and E85. Alternatively, in the context of our model, we can compute the optimal mandates conditional on a maximum ethanol blend ratio of 10%. Such optimal mandates produce a welfare change of $3.18 billion (relative to no biofuel policies). Hence, whatever investment that may be required to permit the larger blend ratio of the optimal mandates in table 4 would increase welfare by a mere $0.17 billion.